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Global eradication of extreme poverty requires absolute convergence of poverty rates worldwide towards zero. Using data for more than a hundred developing countries over 35 years, we conclude that such goal is likely to remain elusive. Rather than absolute convergence, we find club convergence: countries' long-run poverty rates cluster into three or four convergence clubs, depending on the specific poverty measure considered. The club-based country classification that results is different from standard classifications based on per capita income. The lowest-poverty club has seen a steady poverty decline, to levels close to zero by the end of the sample period. The intermediate-poverty club(s) exhibit the largest poverty reduction, especially fast since the mid-1990s. In turn, the highest-poverty club, whose member countries comprise almost half the world's poor in the final year of the sample, evokes a poverty trap: it has seen little change in average poverty over the entire sample period. We find that income plays a bigger role than inequality for club membership, and income growth matters more than initial income; in contrast, initial inequality plays a bigger role than its changes over time. High initial income and low initial inequality almost invariably drive countries into the lowest-poverty club, while weak growth and low initial income are the key drivers of membership in the highest-poverty club. Inequality plays a more substantive role for membership in intermediate-poverty clubs.

Keyword: Absolute Poverty, Convergence clubs, Income growth, Inequality, Developing countries.

JEL Cassification: D31, I3, O11, O4.

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Global eradication of extreme poverty requires absolute convergence of poverty rates worldwide towards zero. Using data for more than a hundred developing countries over 35 years, we conclude that such goal is likely to remain elusive. Rather than absolute convergence, we find club convergence: countries' long-run poverty rates cluster into three or four convergence clubs, depending on the specific poverty measure considered. The club-based country classification that results is different from standard classifications based on per capita income. The lowest-poverty club has seen a steady poverty decline, to levels close to zero by the end of the sample period. The intermediate-poverty club(s) exhibit the largest poverty reduction, especially fast since the mid-1990s. In turn, the highest-poverty club, whose member countries comprise almost half the world's poor in the final year of the sample, evokes a poverty trap: it has seen little change in average poverty over the entire sample period. We find that income plays a bigger role than inequality for club membership, and income growth matters more than initial income; in contrast, initial inequality plays a bigger role than its changes over time. High initial income and low initial inequality almost invariably drive countries into the lowest-poverty club, while weak growth and low initial income are the key drivers of membership in the highest-poverty club. Inequality plays a more substantive role for membership in intermediate-poverty clubs.

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1. INTRODUCTION

The first of the Sustainable Development Goals (SDGs) is the global eradication of extreme poverty by 2030. To achieve it, poverty across developing countries should converge to zero by such date. However, despite the considerable progress made at global poverty reduction over the last two decades, there is still a long way to go: people living below the poverty line of US$1.90 (in 2011 PPP dollars) represent, still in 2018, 8.6% of the world population (652 million people). Moreover, poverty rates display considerable variation between and within developing regions (World Bank, 2020).[1] This prompts the question whether poverty is in fact converging towards zero across the world.

In this paper, we provide an empirical assessment of poverty convergence across more than a hundred emerging and developing countries. Using poverty data from PovcalNet, we consider three different dimensions of absolute poverty (Ferreira et al., 2016): the scale of poverty (as captured by the headcount rate, the poverty measure at the heart of the SDGs), poverty intensity (as measured by the poverty gap), and poverty severity (as measured by the squared poverty gap and the Watts index). For each of these poverty dimensions, our framework allows for four possible scenarios: divergence, absolute convergence, conditional convergence, and club convergence.[2]

At a general level, a dynamic process can be characterized by three ingredients: its initial conditions, its transitional dynamics, and its long-run or steady-state equilibrium (if one exists). Absolute convergence (or β-convergence, Baumol, 1986; Barro and Sala-i-Martin, 1992) means that countries converge to a common steady state in which long-run poverty rates are equalized across the world (Ravallion, 2012). In turn, conditional convergence means that each country converges towards its own long-run poverty rate, which depends on country-specific fundamental factors (e.g., the institutional framework, the degree of openness, the saving rate, or macroeconomic policy). These two processes have in common that initial conditions are

[1] Between 1990 and 2018, the average headcount poverty rate fell from 60.9% to 1.2% in East Asia and the Pacific, from 15.6% to 4.0% in Latin America and the Caribbean, and from 49.5% to 15.3% in South Asia (where the latest available data corresponds to 2015). In Sub-Saharan Africa the poverty rate decreased by almost 15 percentage points between 1990 and 2018, but 38.9% of its population (around 420 million people) still lives below the 1.90 poverty line. Within each region, there are also large differences across countries. For example, in South Asia over 1990-2015, the headcount poverty rate declined from around 44% to 15% in Bangladesh, and from about 9% to almost zero in Sri Lanka. The contrast is even starker in Sub-Saharan Africa, where Zambia saw its headcount poverty rate rise from about 55% to 59%, while Namibia reduced it from about 33% to 14% over the same period.

[2] See Johnson and Papageorgiou (2020) for an extensive and updated review on the different notions of convergence.

irrelevant in determining long-run equilibria and that the effect of transitory shocks is purely temporary, affecting the dynamics of poverty in the short term and along the transition path, but without any effect in the long run.

The concepts of absolute and conditional convergence stem from the neoclassical growth model (Solow, 1956) featuring strictly concave technology and a single, globally stable steady-state equilibrium. However, the presence of heterogeneous agents, imperfect capital markets, or human capital in the neoclassical framework can result instead in multiple equilibria (Galor, 1996), which opens the possibility of club convergence:[3] countries sharing the same fundamentals may converge to different, locally stable long-term equilibria if their initial conditions are sufficiently different. The initial conditions would approximate what Mookherjee and Ray (2001) call "historical self-reinforcement", which could permanently favor one country over another. In this setting, the effect of transitory shocks may be permanent, since they can move a country from one basin of attraction to another, and this in turn gives rise to 'big push' development views (Sachs, 2006; Easterly, 2006), according to which large increases in aid to developing countries may succeed in offsetting the effects of unfavorable initial conditions.

This paper is, as far as we are aware, the first to perform formal tests of the hypothesis of club convergence in absolute poverty. While traditional empirical techniques (borrowed from the empirical growth literature) may be useful to disentangle poverty divergence from absolute or conditional convergence, they are not appropriate to differentiate these situations from club convergence (Durlauf and Johnson, 1995; Islam, 2003). For that purpose, we use the panel clustering testing methodology from Phillips and Sul (2007; 2009). Building on a nonlinear factor model with time-varying loadings, this methodology – which can be easily adapted to almost any type of variable -- allows us to test for a wide range of poverty dynamics: divergence, club convergence, and convergence, whether absolute or conditional.

In contrast with the international community's stated goal of absolute poverty convergence towards zero, using data for a sample of 104 emerging and developing countries over more than three decades we unambiguously reject the hypothesis of absolute convergence. Instead, we find strong evidence of club convergence: four clubs for the scale of poverty (as captured by the

[3] Club convergence is consistent with the evidence that the income distribution across countries has evolved into two peaks (the poorest and the richest), as initially found by Quah (Quah, 1993, 1996) and more recently by Bloom et al. (2003). It is also consistent with the poverty trap literature (Azariadis and Stachurski, 2005; Bowles et al., 2006; Haider et al., 2018), which highlights mechanisms through which poor individuals or countries may get stuck in a low-income equilibrium in which poverty becomes self-perpetuating.

headcount), and three clubs for poverty intensity and severity. For all poverty measures considered, the average poverty rate of the highest-poverty club remains virtually unchanged at very high levels (e.g., between 50% and 60% for headcount poverty) over the last 35 years. Out of the 696 million poor in our sample countries in the final year of analysis, 322 million (i.e., almost half) live in countries belonging to the highest-poverty club of headcount poverty, whose lack of progress at poverty reduction over the sample period effectively makes it akin to a poverty trap.

At the other end, for all poverty measures examined, the average poverty rate of the lowest-poverty club follows a downward trend, approaching zero by the end of the sample. Intermediate-poverty clubs diverge from the highest-poverty club from the mid-1990s on, and show the largest poverty reduction of all clubs over the entire sample.

We find that geography matters for club membership, but it is far from being the only factor at play. For example, Sub-Saharan African countries account for most of the membership in the highest-poverty club, but almost half of all Sub-Saharan African countries belong to other clubs with lower average poverty levels. Moreover, outside the highest-poverty club, membership is geographically quite diverse. We also show that the country ordering defined by the poverty clubs does not amount to a mere partition of the country sample into contiguous subsets according to countries' poverty rates at the end of the period of analysis. In addition, the club-based ordering is also different from those derived from conventional country classifications based on per capita income, such as the World Bank income classification.

All these results hold robustly across the different measures of poverty we examine. Indeed, we find that club membership is remarkably consistent: out of the 104 countries in our sample, three-fourths are allocated to the same club under all four poverty measures considered.

In the second part of the paper, we characterize the effect of income and inequality on countries' likelihood of belonging to a particular club. In line with the existing literature (see references at the end of this section), we assume that these two variables summarize the fundamental factors driving poverty dynamics (and hence club formation). Since our endogenous variable, club membership, is an ordinal discrete variable, we estimate an ordered response model (McKelvey and Zavoina, 1975; Greene and Hensher, 2010) that relates club membership to per capita income and inequality (as captured by the Gini index). We further distinguish between the initial values of the forcing variables and their changes over the sample period, since the formation of clubs may depend on both dimensions.

Using this approach, we can assess the respective roles of initial income and inequality, as well as their changes over time, for countries' poverty club membership. This allows us to address two important questions. First, to what extent is membership just driven by countries' initial conditions, as opposed to their subsequent performance? Second, what is the overall contribution of inequality, as opposed to income, to club membership? Furthermore, we can assess if the answers to these questions are the same for all clubs, or if they are different for high- and low-poverty clubs.

For this purpose, we estimate a general model including all four explanatory variables (initial conditions and changes in both income and inequality), as well as two restricted models -- one including only initial conditions, and another including only income variables – and compare their ability to predict correctly countries' poverty club membership.

Overall, for all four poverty measures considered, we find that the general model fits the data very well. The dominance statistics show that the biggest contributors to the model's overall fit are initial income and its change over time. In turn, the restricted models naturally provide a poorer fit to the data, especially in the case of the model featuring only the initial values of income and inequality. The general model is also quite successful at predicting countries' poverty club membership: between 81 and 96 percent of the sample countries (depending on the poverty measure considered) are selected into the correct club, i.e., the one obtained from the Philips and Sul panel clustering procedure. The restricted model excluding the inequality variables also does fairly well in this regard, suggesting that inequality plays a secondary role in shaping poverty club membership.

Closer examination of the predictive success of the three models by poverty club yields additional insights, which apply to all the poverty measures considered. First, membership in the lowest-poverty clubs is well predicted by all models. However, the restricted model specification featuring only initial conditions does as well or better than the full model in this regard. In other words, the lowest-poverty clubs are dominated by countries that started from favorable initial conditions in terms of income and/or inequality.

Second, country membership in the highest-poverty clubs is very well predicted by the full model. However, the restricted specification featuring only initial income and its growth rate does fairly well too in this regard. This suggests that inequality has not played a major role in driving countries into the highest-poverty clubs.

Lastly, all models tend to predict membership in the intermediate-poverty clubs less well than membership in the highest- and lowest-poverty clubs. The difference in predictive accuracy is relatively modest in the case of the full model, but it is quite large for the restricted specifications, especially for the one featuring only initial conditions, whose predictive performance is disappointing. From these observations we conclude that initial conditions have contributed relatively little to countries' membership in intermediate-poverty clubs, and that the inequality dimension matters more for membership in these clubs than it does for membership in the highest-poverty clubs.

Our paper is embedded in an extensive literature on convergence (recently surveyed by Johnson and Papageorgiou, 2020; Kremer et al., 2021) and on the multidirectional links among poverty, growth and inequality (recently surveyed by Cerra et al., 2021; Marrero and Servén, 2022). Three strands of that literature are especially relevant in our context, namely those respectively concerned with poverty convergence; the formation of convergence clubs; and the contribution of income and inequality to poverty.

Few papers have analyzed the issue of poverty convergence. Moreover, they reach conflicting conclusions. Using PovcalNet data, Ravallion (2012) finds no evidence of convergence among a set of 90 developing countries. However, Sala-i-Martín (2006) reaches the opposite conclusion using data from the World Income Inequality Database (WIID), although he cautions of a certain degree of divergence in some Sub-Saharan African countries (Pinkovskiy and Sala-i-Martin, 2013). More recently, Ouyang et al. (2019) have revisited the issue of poverty convergence using an extended version of Ravallion's data. For their full country sample, they find no evidence of convergence. However, they do find convergence among Sub-Saharan African countries. Overall, poverty convergence remains an open question. We contribute to this literature by bringing the club convergence perspective and offering a formal tests of club convergence in absolute poverty.[4]

In turn, research on the formation of convergence clubs derives from the literature on multiple equilibria (Abramovitz, 1986; Baumol, 1986), and the convergence club approach has been applied mainly to individual income or to country-level GDP per capita (Quah, 1996; Bartkowska and Riedl, 2012; Phillips and Sul, 2009). This paper applies this approach to poverty.

[4] Ouyang et al. (2019) attempt to tackle the possibility of club convergence through some simple tests of region-wise poverty convergence. However, those tests are not informative about club convergence in general, except in the particular case in which club membership is known a priori and driven exclusively by geographic factors.

Importantly, the existence of income convergence clubs does not automatically imply the existence of poverty convergence clubs. The reason is that poverty depends on both mean income and inequality (Bourguignon, 2003). Countries converging to the same income club but following sufficiently different inequality paths could converge to different poverty clubs. Thus, to assess the existence of poverty convergence clubs it is necessary to apply the club convergence approach to poverty itself rather than income, and this is our contribution to the literature on this front.

Another strand of the literature explores the links between income growth and inequality, on the one hand, and poverty, on the other. The bulk of this literature focuses on the poverty-reducing effect of growth and the factors that shape it (Dollar and Kraay, 2002; Bourguignon 2003; Ravallion, 2004; Kraay, 2006; Dollar et al., 2016). Empirically, there is broad agreement that growth reduces poverty, hence fostering aggregate growth is pro-poor (see also Ferreira et al., 2010, Bluhm et al., 2018 and Bergstrom, 2020). In contrast, the contribution of changes in inequality to poverty reduction has generally been found to be much smaller, which probably explains why the literature on the impact of inequality on poverty is more limited, although there are several relevant exceptions, such as Ravallion (2005), Kalwij and Verschoor (2007) or Fosu (2017). More recently, Bergstrom (2020) or Lakner et al. (2020) find evidence supporting the relevant role of declining inequality for poverty reduction. To this literature we contribute by assessing the respective contributions of income and inequality to shaping countries' membership in the different poverty convergence clubs, and how those contributions may vary across clubs.

The rest of the paper is structured as follows. In Section 2, we provide a quick overview of the poverty data used in the paper and conduct a classical convergence analysis. In Section 3, we present the convergence clubs methodology and show the main empirical results for the alternative poverty measures considered. In Section 4, we estimate an ordered response model to analyze the relation between club membership and the two main drivers of poverty: income and inequality. Finally, Section 5 presents the main conclusions.

2. ABSOLUTE POVERTY AROUND THE WORLD

We consider the following family of additive poverty measures, denoted by P (Watts, 1968; Sen, 1976):

$$P(z) = \int_0^{P0} \Omega[y(q); z]\, dq, \tag{1}$$

where z is the poverty line, $y(q)$ denotes the income of the q^{th} percentile of the income distribution at time t (the time sub-index is omitted if not needed) and P0$= F(z)$, with $F(\cdot)$ the cumulative distribution of income, is the headcount poverty rate. For $\Omega(y(q); z) = (z - y(q)/z)^{\theta}$, we obtain the Foster–Greer–Thorbecke class of poverty measures (Foster et al., 1984), which includes the headcount ($\theta = 0$), denoted P0 below, the poverty gap ($\theta = 1$), denoted P1, and the squared poverty gap ($\theta = 2$), denoted P2. For $\Omega(y(q); z) = \ln[z/y(q)]$, we obtain the Watts index, denoted W.

Each of these measures provides information on a different dimension of absolute poverty. The headcount captures the *scale* of poverty, i.e., the proportion of the population with income below the poverty line z. It does not change in response to changes in the income distribution below the poverty line, i.e., when a very poor individual becomes less poor or when a poor individual becomes even poorer. In turn, the poverty gap provides a measure of poverty *intensity*, as it shows the (average) shortfall of the income of the poor relative to the poverty line. The squared poverty gap and the Watts index capture the *severity* of poverty. The squared poverty gap weights the income gap of each household by the size of the gap itself, hence increases in the resources of the poorest individuals reduce overall poverty by more than do changes in the resources of less-poor individuals. Finally, the Watts index places a bigger weight than the squared poverty gap on very low incomes, and a lower weight on the incomes of less-poor individuals.[5]

Time-series data on these poverty measures are taken from PovcalNet, using a poverty line of US$1.90 per individual per day at 2011 PPP (Ferreira et al., 2016), which replaces the earlier threshold of US$1.25 per individual per day at 2005 PPP.[6] PovcalNet's poverty estimates are constructed from household surveys. To allow comparisons over time, PovcalNet reorganizes the available survey data into reference years, typically at three-year intervals. In countries where survey data are not available on an annual basis, growth rates from national accounts are used to project consumption or income forward and backward, obtaining "interpolated data". The first

[5] Under lognormality, the Watts index has also a useful interpretation as the time to exit poverty – i.e., the number of years it would take for a poor household to grow out of poverty given a hypothetical, steady growth of annual income (or consumption). It can be shown that the exit time is exactly given by the Watts index divided by the income growth of the poor.

[6] Poverty estimates are homogenized using PPP exchange rates for household consumption from the 2011 International Comparison Program.

reference year is 1981 and the most recent one is 2018. However, after 2015 South Asia's available surveys cover less than 50% of the region's total population (Aguilar et al. 2020). Thus, to allow meaningful comparisons across regions and countries, we focus on the 1981-2015 period.

From the initial set of 164 countries, we retain only those whose surveys report poverty information at the national level, and drop those with solely rural or urban coverage. To keep the focus on poverty, we also disregard rich countries (Australia, Japan, Israel, United States, Canada and western European countries), since their absolute poverty levels are zero or very close to zero for all measures and years in the sample. Lastly, we drop countries with incomplete time series.[7] Thus, our final sample consists of 1,248 observations, comprising 104 developing countries over the period 1981-2015 at three-year intervals (see Appendix A for details).[8]

Table 1 reports descriptive statistics for the four poverty measures in 1981 and 2015, as well as their annual change over the period. Figure 1 shows the time path of their respective cross-sectional averages as well as the 25th and 75th percentiles. Several facts common to all four poverty measures are worth noting.

First, their respective cross-country averages follow similar trends. Between 1981 and 1993, average P0 remained relatively stable at around 34%, while the averages of the other poverty measures show a very slight decline, with P1, P2 and W hovering around 15%, 9% and 25%, respectively. However, between 1993 and 2015 the averages of all four measures exhibit a substantial reduction. Average P0 falls from 32% in 1993 to 19% in 2015, which amounts to a reduction of 0.71 percentage points (p.p.) per year. Over the same period, average P1, P2 and W similarly decline by 0.38, 0.24 and 0.63 p.p. per year, respectively. Second, the sample distributions of the four poverty measures are skewed to the right, as median poverty is in all cases much lower than average poverty. The third fact is the reduction in the between-country dispersion of absolute poverty over the sample period. All four poverty measures exhibit much lower standard deviation in 2015 than in 1981 (see Table 1). The time path of their 25th-75th

[7] For that reason, we remove Sao Tome and Principe, South Sudan and Timor-Leste, as well as the former Yugoslavia and Soviet Union countries. Ravallion (2012) also removes former Yugoslavia and Soviet Union countries because they display atypical behaviour due to their transition from socialist to market economies.

[8] As poverty displays considerable inertia, the lack of annual information is not a big hurdle for our purposes. Before 2010, Povcalnet only provides poverty information at three-year intervals. Reference years are 1981, 1984, 1987, 1990, 1993, 1996, 1999, 2002, 2005, 2008, 2010, 2011, 2012, 2013 and 2015. To build a time series with spells of constant length, as required for the club convergence analysis, the best option is to use data every three years. Hence, from the original information we exclude 2010 and 2012, and use the data from 2015 to approximate the information for 2014. Using instead the average of 2013 and 2015 to approximate 2014 does not materially affect the results.

percentiles (Figure 1) reveals that dispersion decreases markedly after 1993. Moreover, the decline is more intense for poverty intensity (P1) and poverty severity (P2 and W) than for the poverty headcount.

Figure 2 shows the relationship between the annual change in poverty (in p.p.) between 1981 and 2015 and its initial level (in 1981) for the four poverty measures considered (i.e., absolute β-convergence graphs familiar from the empirical growth literature). The four scatter plots exhibit negative slopes, so that, on average, countries with higher initial poverty tended to reduce their poverty rate by more than did countries with lower initial poverty.

It would be tempting to interpret these negative (and significant) slopes as indicative of β-convergence. However, cross-sectional regressions of poverty changes on initial poverty like those underlying Figure 2 do not offer solid ground for such conclusion The reason is that they may yield negative and significant slope estimates in settings in which some countries are converging but others are not (Bernard and Durlauf, 1996). The same result may arise in settings in which different (groups of) countries converge to different steady states (Durlauf and Johnson, 1995).[9] A rigorous assessment of poverty convergence requires empirical tools better suited to deal with such settings. This is the task undertaken in the next section.

3. POVERTY CONVERGENCE CLUBS

A poverty convergence club consists of a set of countries whose poverty rates may differ over an extended period, but converge to one another in the long-run (Galor, 1996).[10] In general, poverty dynamics (just like the dynamics of income or inequality) is governed by a set of economic fundamentals, such as technology, fiscal policy, trade openness or market structure (Johnson and Papageorgiou, 2020). The key difference between club convergence and other forms of convergence, such as conditional convergence, is that initial conditions also play a role in the dynamic process. Thus, differences in initial conditions can become permanent: countries with similar structural features may converge to different long run poverty rates if their initial conditions are sufficiently different.

[9] See also Quah (1993, 1996) for additional concerns with these cross-section regression-based tests and their relation with absolute convergence.

[10] Thus, absolute convergence implies that all countries belong to a single club.

3.1. The statistical model

To test for club convergence along each of the poverty measures described in the previous section, we follow Phillips and Sul (2007) (P-S from now on). We assume a generic latent factor model without specifying its origin and its relationship with income or inequality,

$$P_{it} = \delta_{it} \mu_t, \tag{2}$$

where P_{it} is a particular measure of absolute poverty for country i at time t. The term μ_t is a common long-run trend capturing forces affecting poverty in all countries, such as technological progress, global trade or international commodity prices.[11] In turn, δ_{it} is a country-specific time-varying loading factor that captures the transition path of country i to the common long-run trend μ_t, reflecting idiosyncratic characteristics related to, for example, technology adoption, macroeconomic policy, institutional quality or geography.

With a view to empirically testing for club convergence, it is convenient to define the relative transition coefficient p_{it}, which measures poverty relative to the world average:

$$p_{it} = \frac{P_{it}}{\frac{1}{N}\sum P_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum \delta_{it}}, \tag{3}$$

which eliminates the common trend μ_t by rescaling the loadings δ_{it} in terms of their cross-section average. Thus, the transition coefficient measures both the behaviour of country *i* relative to the average and its deviation from the common path.

Following P-S, we assume that the factor loading δ_{it} takes the following form:

$$\delta_{it} = \delta_i + s_{it}\varepsilon_{it}; \text{ with } s_{it} = \frac{s_i}{\mathrm{L}(t)\cdot t^{\alpha}}; \text{ for } t \geq 1, s_i > 0, \tag{4}$$

Where s_i is a time-invariant parameter, ε_{it} is an iid standard normal random variable, $\mathrm{L}(t)$ is a slowly-varying function of time (P-S use $\ln t$ specifically), and α is a parameter that can be positive or negative depending on whether there is convergence or not. For the case of convergence (with $\alpha \geq 0$), the higher is α, the faster s_{it} tends to zero, and the faster is the convergence of δ_{it} towards δ_i.

It is easy to see that under the null hypothesis of convergence $\lim_{t\to\infty} \delta_{it} = \bar{\delta_i} = \bar{\delta}$ for all i, while under the alternative hypothesis $\lim_{t\to\infty} \delta_{it} \neq \bar{\delta}$ for at least some i. Using (4), testing the null of

[11] We should note that the Phillips-Sul approach to identifying convergence remains valid regardless of the order of integration of the variables under consideration (Apergis and Payne, 2019; Johnson and Papageorgiou, 2020).

convergence is equivalent to testing whether $\bar{\delta_i} = \bar{\delta}$ for all i and $\alpha \geq 0$, while the alternative is $\bar{\delta_i} \neq \bar{\delta}$ for all i, or $\alpha < 0$ (or both). Using the relative transition coefficients p_{it} and their dispersion, convergence implies that $p_{it} \to 1$ as $t \to \infty$ for all *i*. Alternatively, the cross-sectional variance of p_{it} under the null, $\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N}(p_{it} - 1)^2$, must tend to zero as *t* grows without bound. The latter condition is the one used by P-S to prove that testing for convergence is equivalent to a one-sided test on the estimated b coefficient in the following regression (referred as a *log-t* regression in P-S)[12]:

$$\log\left(\frac{\sigma_1^2}{\sigma_t^2}\right) - 2\ln\big(ln(t)\big) = a + b\ln t + u_t, \tag{5}$$

where σ_1^2/σ_t^2 is the cross-sectional variance in the initial period relative to the variance in period t, $b = 2\alpha$, and α is the convergence term in (4).

Testing for convergence using equation (5) has the following intuition. Under the null hypothesis of convergence, the ratio σ_1^2/σ_t^2 diverges towards infinity, as σ_1^2 is a positive constant and σ_t^2 tends to zero. Thus, under the null hypothesis of convergence, b in (5) must be non-negative: if $b = 0$, the ratio σ_1^2/σ_t^2 diverges as $2\ln(ln(t))$, and if b>0, the ratio also diverges as $b\ln t$ (a faster speed). However, under the alternative hypothesis (lack of convergence), P-S prove that σ_t^2 tends to a positive quantity. Hence, the dependent variable in (5) must diverge to minus infinity, which requires $b < 0$.

Since b is a scalar, the null hypothesis of convergence ($b \geq 0$) can be easily tested against the alternative ($b < 0$) with a one-sided t-test on the estimated b in (5), using HAC standard errors. Thus, if the computed t-statistic t_b is above -1.65, the null hypothesis of convergence cannot be rejected. In this case, the distinction between absolute and conditional convergence rests on the magnitude of the estimate of b: $b \geq 2$ implies absolute convergence, while $0 \leq b < 2$ implies conditional convergence (see Phillips and Sul, 2009, section 4.2). Conversely, if the t-statistic is below -1.65, the null hypothesis of convergence is rejected at the 5% significance level.

However, rejection of the null hypothesis can imply either overall divergence, or convergence among subgroups of countries (i.e., club convergence). The testing procedure in P-S is embedded within a clustering algorithm for detecting potential convergence clubs, i.e., to

[12] See Appendix B in P-S for details.

determine whether $\bar{\delta_i} = \bar{\delta}$ for a set of countries i and $\alpha \geq 0$. When starting the algorithm, whether a country is assigned to a particular convergence club depends on the outcome of the one-sided t-test on b in the *log-t* regression performed for different sub-samples.[13]

3.2. Empirical implementation

Implementation of the P-S approach requires a balanced panel dataset. As described in Section 2, we use data from PovcalNet on the different measures of poverty over the 1981-2015 period, spaced at 3-year intervals. We estimate a separate factor model (equation (2)) for each of the four alternative poverty measures considered. In each case, the transitional coefficients (equation (3)) are constructed using filtered series to mitigate noise and cyclical fluctuations.[14] An issue is the proper choice of filter and degree of smoothing. P-S uses the HP filter with a smoothing parameter of 400 for annual data. However, Ravn and Uhlig (2002) find that, for annual data, the smoothing parameter of the HP filter should equal 6.25. They also formulate a rule for the choice of smoothing parameter for other data frequencies. Following that rule, for our triennial data we obtain a smoothing parameter of $(4 \cdot 3)^4 = 0.0778$. The qualitative results reported below remain largely unchanged if a locally larger smoothing parameter is employed.

Next, using the numerical clustering algorithm from P-S, we estimate iteratively equation (5) in order to classify countries either into convergence clubs or as divergent units. For each poverty measure, Table 2 shows the results from estimation of equation (5) (i.e., the estimates of b and the associated *t*-statistics) over the full sample and for each club, the number of countries, and the average levels of poverty at the beginning and end of the period, along with its annual change.

[13] The basic procedure of the clustering algorithm is the following. First, arrange the panel in descending order according to the poverty rate at the end of the sample period. Second, run the log-t regression and test for overall convergence. If the hypothesis of overall convergence is rejected, the two countries showing the highest poverty rates are selected and other countries are added one by one, running the log-t regression until a t_b larger than -1.65 is found. The group of countries that maximizes t_b comprises the so-called core group. If $t_b > -1.65$ does not hold for the first two countries, the algorithm starts again with the next two countries, adding each of the remaining countries at a time to the core group and running the log t-regression again. All units with $t_b > -1.65$ are included in the core group, thus forming the first convergence club. Then the process is repeated for all the countries not in the convergence club, in order to classify them either as convergence clubs or divergent units. For a further description of the clustering algorithm, see Section 4.3. in P-S, and Appendix 1 in Borsi and Metiu (2015) or Schnurbus et al. (2017).

[14] In our case, an additional difficulty with the filtering is that the filtered poverty rate may not lie in the range between zero and one. Moreover, the clustering algorithm tends to perform poorly for values of poverty very close to zero, which often leads to finding a large number of clubs with very few member countries in each, whose poverty rates are all converging to zero. To avoid these problems, we restrict the filtered series to the range [0.01, 1]. Moreover, following the recommendation in P-S for sample sizes below 50 in the time dimension, we discard the first 1/3 time-series observations to improve the power of the convergence tests.

We obtain a total of four clubs for the headcount poverty rate, and three clubs for each of the other three poverty measures. The detailed list of countries belonging to each club is shown in Table 3.

To present the results, in Table 2, clubs are arranged in descending order of long-run poverty, i.e., Club 1 is the club with the highest long-run levels of poverty. For P0, P1, P2 and W, the average levels of poverty in 2015 are 49.2%, 20.9%, 14.1% and 37.3% in the highest-poverty clubs, and 1.2%, 1.4%, 0.5% and 1% in the lowest-poverty clubs, respectively. For illustrative purposes, in Table 2 we also present the β coefficients obtained from club-specific β-convergence regressions (i.e., like the regressions in Figure 2 but done separately for each club).

For the four poverty measures, the t-statistics are well below the critical level of -1.65 for the full sample: -27.5 for P0, -24.9 for P1, -33.0 for P2 and -15.7 for W. Thus, in spite of the appearance of absolute convergence that a naïve look at Figure 2 might suggest, more careful analysis unambiguously rejects the null hypothesis of absolute convergence for all four poverty measures considered. Hence, our results are a reminder that conventional beta-convergence analysis of absolute poverty can easily lead to misleading conclusions in the presence of convergence clubs (Durlauf and Johnson, 1995).

In turn, for each club and for all poverty measures considered, the estimated t-statistics of equation (5) are above -1.65, consistent with the hypothesis of convergence within each club. Moreover, the higher the estimated b, the higher the implied speed of convergence within each club (i.e., recall that $b = 2\alpha$ and α is a measure of convergence speed from equation (5)). In general, we observe higher speeds of convergence (i.e., higher levels of b, according to Table 2) within lower-poverty clubs. These results are consistent with the β-convergence estimates also shown in Table 2: for all poverty measures considered, they are much larger for the lowest-poverty clubs (ranging between 2.8-2.9) than in the highest-poverty clubs (for which they range between 1.1 and 1.9).

Figure 3 shows the evolution of the cross-sectional mean for each poverty measure and club. For the highest-poverty club (Club 1 in all measures), average poverty shows little change between the beginning and the end of the sample period – it remains at high levels throughout. For the lowest-poverty club (Club 4 for P0 and Club 3 for P1, P2 and W), the trend is also similar for all poverty measures: average poverty shows a slight but persistent reduction throughout the period to reach an average of almost zero in 2015.

Intermediate clubs (Clubs 2 and 3 for P0 and Club 2 for the other measures) show the largest extent of poverty reduction over the entire sample. For headcount poverty, the comparison between Clubs 2 and 3 is interesting. Until the mid-1990s, their average poverty levels were fairly stable and roughly similar. Thereafter, however, headcount poverty declines sharply among Club 3 countries, even approaching the levels of Club 4, while it undergoes a more modest reduction among Club 2 countries.[15].

More broadly, the club composition provides a mixed perspective on the progress with global poverty eradication. Only the countries belonging to the lowest-poverty club appear to be converging to near-zero poverty. Table 2 shows that, depending on the poverty measure under consideration, they roughly represent between one-third and two-thirds of the country sample. In turn, countries in the intermediate-poverty clubs are making progress towards lower, but not zero, long-run poverty rates. At the other end, however, countries belonging to the highest-poverty club have seen little poverty reduction in the last 35 years, which suggests that they may be caught in a poverty trap.

The distribution of the world's poor across clubs at the end of the sample period allows a more precise view on the prospects for global poverty eradication. We can compute it by summing the number of poor across each club's member countries in 2015.[16] Figure 4 shows the distribution that results for each of the poverty measures considered. The total number of poor in our sample in 2015 equals 696 million. Out of that total, 322 million (46%) live in countries trapped in Club 1 of headcount poverty. At the other end, only 24 million live in countries approaching complete poverty eradication (i.e., belonging to Club 4 of headcount poverty). Moreover, Figure 4 also shows that, of those 322 million trapped in a high-poverty equilibrium, about 83% (268 million) appear to be trapped also in a path of persistently high poverty intensity (as implied by their allocation to Club 1 of the poverty gap), and about 50%

[15] For instance, within Club 2 we find countries such as Chad, Senegal and Uganda (members of Club 2 in all poverty measures), which reduced their headcount poverty rates 38, 22 and 23 p.p., respectively, between 1996 and 2015, but their poverty rates in the final year are still far from zero. However, within Club 3 there are countries that start in 1981 with poverty levels similar to those observed in countries of clubs 1 and 2 and, after 35 years, have managed to bring their poverty rates close to zero. This is the case, for example, of Guatemala, China or Vietnam, which pertain to Club 3 under all poverty measures. In addition, for the poverty gap, countries belonging to Club 2 exhibit a peculiar behavior: the club's average poverty trajectory crosses that of Club 1 in 1999, at a level of P1 around 25%. This is because several countries from Club 2 (i.e., Guinea, Mali or Sierra Leone) started in 1981 with very high levels of P1 (above 45%) and managed to reduce them sharply by 2015. In contrast, other countries from Club 1 (i.e., Benin, Madagascar or Lesotho started with smaller poverty gaps (below 26%) but failed to reduce them by the end of the sample period.

[16] We calculate the number of poor in each country multiplying its 2015 headcount poverty rate by its total population in the same year. Both magnitudes are shown in Table A1.

(170 million) are stuck in persistently high poverty severity as well (as implied by their allocation to Club 1 of the squared poverty gap and the Watts index).[17] Overall, the conclusion is that global poverty eradication is likely to remain elusive on current trends.

Geographic location matters for club membership (see Table B1 in Appendix B), especially for the highest-poverty club, although it is far from being the only factor at play. For instance, while SSA countries account for most of the membership in Club 1 (i.e., 92%, 77%, 82% and 88% of the member countries for P0, P1, P2 and W, respectively), almost half of all SSA countries belong to clubs with lower poverty levels (see Table 3). Moreover, for the other clubs, membership is geographically more diverse. For instance, Latin America and the Caribbean (LAC) countries account for most members in the lowest-poverty clubs, representing almost one-third of the total for all poverty measures and, in general, we find that clubs with intermediate poverty levels include countries from all regions – e.g., Belize and Honduras from LAC, Papua New Guinea from East Asia and Pacific (EAP), Yemen from the Middle East and North Africa (MENA), and Comoros and Eswatini from SSA.

To conclude this section, it is important to emphasize that the poverty clubs we identify do *not* reflect a mere partition of the country sample into contiguous subsets according to countries' poverty rates at the end of the period of analysis. If that were the case, every country in Club 1, for example, would exhibit higher poverty in 2015 than every country in Club 2, and the same would apply to Club 2 vs Club 3, and so on. Figure 5 clearly shows that this is not the case: there is considerable overlap between the ranges of 2015 poverty rates of the various clubs, even between those of the highest- and lowest- poverty clubs. This serves to underscore the fact that the clubs are defined by countries' (estimated) long-run poverty rates, themselves driven by poverty trends over the sample period, and not only by the levels of poverty at any particular moment of the sample.

It is also worth noting that the country ordering defined by the poverty clubs is different from those derived from conventional classifications based on per capita income. Figure 5 illustrates the case of the World Bank income classification as of 2015 (the final year of our sample), comparing its country groups – high and upper-middle income (combined in the figure into a single group), lower-middle income, and low income – with the clubs identified by our

[17] These observations are based on the fact that, as Table 3 shows, all countries belonging to Club 1 under P1, P2 and Watts also belong to Club 1 of headcount poverty. The only exceptions are Djibouti and Suriname, which belong to Club 2 under P0. However, their combined total number of poor in 2015 is just 0.28 million, which is immaterial for the calculations in the text.

procedure. While there is a good deal of commonality between both classifications, it is far from a perfect match, which confirms that the club-based clustering provides independent information relative to that provided by the income-based clustering.

3.3. Concordance among poverty measures

Since the four poverty measures under consideration capture different poverty dimensions, one may wonder how consistent is club membership across them. Is the clustering of countries broadly similar under the four poverty measures, or is it very different? In the former case, our findings regarding the country composition of the various clusters would be robust across the different poverty dimension considered, while in the latter we would not be able to draw firm conclusions on countries long-run poverty performance, as countries could be approaching high long-run poverty for some poverty dimensions, and low long-run poverty for others.

We use three statistics to assess the concordance between the club memberships obtained for alternative poverty measures: the Spearman rank correlation, the Kappa statistic (Cohen 1960) and the concordance correlation coefficient (Lawrence and Lin 1989). The latter two statistics merit some explanation. The Kappa statistic is typically used to measure the degree of agreement of the ratings (in our case, club membership) given by two different raters (in our case, poverty measures), corrected for how often the raters may agree by pure chance. Thus, a Kappa equal to zero means that there is only random agreement between raters, a negative value means that there is less agreement than would be obtained by chance, and a value of one implies that there is a complete agreement between the raters.[18]

In turn, the concordance correlation coefficient evaluates the degree to which pairs of observations fall on the 45-degree line through the origin. Its values go from +1 (perfect concordance) to -1 (perfect discordance), and values near zero indicate no concordance. We should note that the statistic is designed for continuous variables, and thus its application to club membership here is just for illustrative purposes.

[18] According to Fleiss (1971), values of Kappa over 0.75 reflect an excellent degree of concordance, values between 0.4 and 0.75 reflect fair to good agreement, and values below 0.4 indicate poor agreement. An alternative guideline is provided by Landis and Koch (1977), where the value of the kappa coefficients is interpreted in terms of strength of agreement as follows: 0.01-0.20 slight; 0.21-0.40 fair; 0.41-0.60 moderate; 0.61-0.80 substantial; 0.81-1.00 almost perfect.

Table 4 shows the results of pairwise comparisons using these statistics.[19] Overall, all three statistics suggest a high degree of concordance in club membership across the different measures of poverty. All Spearman correlations exceed 0.83, while the concordance correlations exceed 0.85, and the Kappa coefficients are around 0.70, close to the range of "excellent" concordance (Fleiss 1971). According to all three statistics, the highest concordances arise when comparing club membership under the poverty gap and the squared poverty gap, while the lowest arise when comparing club membership under the poverty gap and the Watts index.

However, it is informative to go beyond these statistics and assess concordance country by country. Table B1 in Appendix B reports club membership for each country under each poverty measure. Out of the 104 sample countries, 77 (i.e., three-fourths of the sample) are allocated to the same club under all four poverty measures. Of these 77 countries, 16 belong to Club 1 (the highest poverty club) under all four poverty measures considered. They are all located in the SSA region, with the single exception of Haiti. Nine other countries consistently belong to Club 2 (intermediate poverty) -- 7 from SSA, 1 from EAP and 1 from LAC. Finally, the largest group of countries (52) with perfectly coherent classification is found in the lowest-poverty club regardless of the poverty measure considered: 17 are from the LAC region, 11 from the EAP region, 8 from the MENA region, 5 from the ECA region, 4 from the SA region and 7 countries are from SSA.

For the remaining 27 countries (one-fourth of the sample), club membership varies (slightly) depending on the particular poverty dimension considered. For example, of the 26 countries belonging to Club 1 of headcount poverty, five (Zimbabwe, Yemen, Republic of Congo, Nigeria and Liberia) belong also to Club 1 of P1 but to Club 2 of at least one measure of poverty severity (P2 or W), while six other countries (Niger, Sierra Leone, Mali, Guinea, Tanzania and Burkina-Faso) belong to Club 2 of both poverty intensity and severity. Two countries (Djibouti and Suriname) belong to Club 2 of P0 and to Club 1 of P1 and of at least one measure of poverty intensity. Nine other countries (Syria, Kiribati, South Africa, Honduras, Ethiopia, Laos, Vanuatu, Botswana and Bangladesh) belong to Club 2 of P0 and to Club 3 of P1 and of at least one measure of poverty intensity (P2 and/or W). The remaining six countries (India, Colombia, Bolivia, Ghana, Gabon and Romania) are members of Club 3 of headcount poverty, and belong

[19] To facilitate the comparisons, we merge headcount poverty clubs 3 and 4 into a single club so that the number of clubs is the same under all four measures of poverty.

instead to the intermediate club (Club 2) of the Watts index. It is worth noting that all countries belonging to Club 4 of headcount poverty also belong to the lowest-poverty club (Club 3) under all other poverty measures.

4. POVERTY CLUB MEMBERSHIP, INCOME AND INEQUALITY

What drives the formation of poverty clubs, and countries' membership in them? In principle one could think of a host of possible fundamental factors. However, from (1) above, poverty can be seen to be a function of mean per capita income and a general measure of inequality. Thus, whatever those fundamental factors happen to be, their influence on the formation of poverty clubs must be primarily channelled through mean income and inequality.

More concretely, let $y_{it}(q)$ denote the income of the *q*-th percentile of the income distribution. It can be expressed as $y_{it}(q) = \bar{y}_{it} L_{it,q}(q)$, where $\bar{y}_{it}$ is mean per capita income, L_{it}(.) denotes the Lorenz curve and $L_{it,q}$ its derivative at the *q*-th percentile. Plugging this expression for $y_{it}(q)$ into (1), we get $P_{it} = \int_0^{P0} \Omega\big(\bar{y}_{it} L_{it,q}(q), z\big)\, dq$. Under lognormality, which is commonly taken to be a fairly good approximation to the actual distribution of income (see e.g., López and Servén 2006), the function $\Omega(\cdot)$ can be further expressed in terms of $\log(\bar{y}_{it})$, $\log(z)$ and the Gini index for P0, P1 and P2, while the Watts index is itself already defined in such terms.

This analytical framework underlies an extensive empirical literature that has sought to quantify the respective contributions of income and inequality to poverty (Bourguignon, 2003; Kraay, 2006; Ferreira, 2012; Ravallion and Chen, 2010 or Dollar and Kraay, 2002, among many others). Generally, this literature employs a linear (or log-linear) specification, such as $P_{it} = \alpha_i + \gamma log\bar{y}_{it} + \varphi G_{it} + v_{it}$, where inequality G is typically measured by the Gini index.

Using this framework, we can quantify the respective roles of income and inequality in determining the club membership of each country. For both variables, we distinguish between their initial conditions and their changes along the transition, since they may have different effects on the formation of poverty clubs. We first review the descriptive evidence, and then turn to the estimation of an ordered logit model of poverty club membership.

4.1. Preliminary evidence

We use mean per capita income expressed in US dollars per day (PPP-adjusted) as a measure of income, and the Gini index as a measure of inequality, both extracted from PovcalNet. Table 5 shows, for each club and poverty measure, the average levels of income and inequality for the initial and final year of the sample period, as well as their annual growth (annual change in the case of the Gini index).[20]

A preliminary inspection of Table 5 suggests that club formation is related to both the initial levels and dynamics of income and inequality. In most cases (but not all), the lower-(higher) poverty clubs exhibit higher (lower) initial average income levels. In turn, they invariably exhibit higher (lower) average income growth and, therefore, a higher (lower) average level of income at the end of the period. Across all poverty measures, average income growth is negative for the highest-poverty club (Club 1), while it reaches around 2% per year for the lowest-poverty club (Club 4 for P0, and Club 3 for the other measures).

The lower-(higher) poverty clubs also start from lower (higher) initial inequality levels. In contrast, the annual change in average inequality does not seem to vary across clubs in the same systematic way income growth does. However, it is worth noting that the levels of inequality have decreased during the sample period across all clubs and for all poverty meassures, although the reduction appears more marked for the intermediate club (Club 2). This faster inequality decline may have been a relevant contributor to the relatively fast decline of the average poverty rate of Club 2 shown in Figure 3 above for the cases of P1, P2 and W.

4.2. An ordered response model of poverty club membership

To get a more rigorous quantitative assessment of the respective roles of income and inequality in poverty club formation, we estimate an empirical model of poverty club membership. Membership is an ordinal discrete variable which takes values from 1 to 4 for P0 and from 1 to 3 for the other poverty measures. Thus, we estimate an ordered logit model relating club

[20] PovcalNet provides interpolated information on mean income (thus, we have data for 1981 and 2015 in all cases), but it does not provide interpolated information on the Gini index and other inequality measures. When 1981 and/or 2015 data on the Gini index are not available, we use the value from the survey closest to the missing year.

membership, as obtained from the Philips and Sul clustering approach in Section 3, to initial conditions and changes in mean income and the Gini index.[21]

More specifically, the dependent variable, poverty club membership of country *i*, denoted C_i, can take a value $c \in \{1,2 \dots N\}$ (where *N* equals 4 for P0, and 3 for P1, P2 and W). Club membership is a discrete function of an unobserved latent variable, denoted by P_i^*, which represents the steady-state level of poverty. The function is parameterized by a set of thresholds, μ_j, with $j \in \{1,2 \dots N-1\}$, and takes the following form:

$$C_i = \begin{cases} 1, if\ P_i^* \leq \mu_1 \\ 2, if\ \mu_1 < P_i^* \leq \mu_2 \\ \quad \dots \\ N, if\ P_i^* > \mu_{N-1} \end{cases} . \tag{6}$$

The latent variable P_i^* is modelled as (McKelvey and Zavoina, 1975):

$$P_i^* = Z_i + \varepsilon_i, \tag{7}$$

where $Z_i = \sum_{k=1}^{K} \gamma_k X_{ki}$ comprises a set of K observed explanatory variables, and ε_i is a random disturbance.. The variables included in X_k should capture the factors driving poverty club membership – initial conditions and structural characteristics of the economy. As noted earlier, it is reasonable to assume that those factors are conveniently summarized by income and inequality – specifically, by their initial values and their changes over time. Hence, we estimate the following reduced form for P_i^*:

$$P_i^* = \underbrace{\beta_1 logy_{it_0} + \varphi_1 G_{it_0} + \beta_2 \Delta logy_i + \varphi_2 \Delta G_i}_{Z_i} + \varepsilon_i, \tag{8}$$

where y_{t_0} and G_{t_0} respectively denote the initial values of mean income and the Gini index, and $\Delta logy_i$ and ΔG_i are their changes over the sample period.

This framework allows us to address two issues of interest. First, how big is the role of initial conditions relative to that of transitory factors (as captured by the changes over time in income and the Gini index) in determining club membership? This is of interest from a policy perspective – while initial conditions are given, there may be ample scope for policy interventions

[21] A similar approach is taken by Bartkowska and Riedl (2012), who estimate an ordered logit model to investigate whether initial conditions are responsible for income club formation in Europe.

affecting the transition. Hence, it is useful to know to what extent initial conditions shape long-run club membership.

Second, how big is the role of inequality in determining poverty club membership? The empirical literature referenced in the introduction generally concludes that observed poverty trends are largely driven by changes in mean income, with inequality playing a relatively minor role. Our empirical setting allows us to verify if the same conclusion applies to the formation of poverty clubs, and whether the conclusion varies across clubs and / or across poverty measures.

To assess both of these issues, we can compare the results from estimating the full model (8) with those from two suitably restricted models, the first one including only initial conditions and the second only income variables:

$$P_i^* = \beta_{11} logy_{it_0} + \varphi_{11} G_{it_0} + v_i, \tag{9}$$

$$P_i^* = \beta_{12} logy_{it_0} + \beta_{22} \Delta log\mathrm{y}_i + w_i. \tag{10}$$

The larger the difference between the explanatory powers of models (8) and (9), the more relevant is the role of income and Gini index changes, given initial conditions, in shaping countries' poverty club membership. Likewise, the larger the difference between the explanatory powers of models (8) and (10), the more relevant is the role of the initial Gini index and its subsequent changes, given income.

We assume the error terms in (8)-(10) follow a logistic distribution, and estimate the parameters of the above equations and the thresholds μ_j in (6) by maximum likelihood. We can then compute the probability that the latent variable P_i^* falls within the various threshold limits estimated, for each model and poverty measure. In this setting, this is equivalent to estimating the probability that the ordered variable C_i takes a particular discrete value c,

$$Pr(C_i = c) = \frac{\exp(Z_i - \mu_{c-1})}{1 + \exp(Z_i - \mu_{c-1})}, \tag{11}$$

where $c \in \{1,2,3,4\}$ for P0, and $c \in \{1,2,3\}$ for P1, P2 and W.

Tables 6 and 7 report the parameter estimates of equations (8)-(10) for headcount poverty and for the other poverty measures, respectively.[22] In general, all coefficients are significant and with the expected signs. The positive signs of the coefficients on initial income and income growth indicate that the probability of belonging to lower-poverty clubs increases with both dimensions of income. The negative signs of the coefficients on the initial level of inequality and its change over time indicate the opposite, in line with most of the existing literature.

To provide a metric for the point estimates, we can recover the odds ratio for each variable by taking the exponential of its estimated coefficient. We provide an illustration of the odds ratios using the full model estimates for the case of headcount poverty (first column of Table 6).[23] For instance, a 1% increase in initial income (e.g., raising it from 10 to 10.10 dollars per day), holding the rest of the variables constant, raises the odds of belonging to the lowest-poverty club (Club 4) relative to the rest (clubs 2, 3 and 4) by 9% ($e^{0.09} = 1.09$). Similarly, the odds of belonging to the highest-poverty club (Club 1) decrease by 30% when the growth rate of income increases 0.1 p.p. per year ($1 - 1/e^{3.60 \cdot 0.1} = 0.30$). Over the 34-year sample period (i.e., between 1981 and 2015), this is equivalent to an income growth of 3.4%, which should be compared with the average growth rate of the entire sample ($1.29 \cdot 34 = 44\%$, see Table 5). This simple quantitative exercise shows the importance of income growth for escaping extreme poverty.

As for the Gini index, the odds of belonging to the highest-poverty club, relative to the rest, decrease by 25% when the initial Gini index decreases 1 p.p. ($1 - e^{-0.28} = 0.25$). Likewise, the odds decrease 29% following an annual reduction of 0.1 p.p. in the Gini index $1 - e^{-\frac{3.47}{10}} = 0.29$). Such annual reduction would entail a drop in the Gini index of 3.4 p.p. over the 34-year sample period.

Tables 6 and 7 also report McFadden's pseudo-R2, which summarizes the overall explanatory power of each model. For the full model (8), the values are quite high, regardless of the poverty

[22] Note that the estimates are computed on a reduced sample of 94 countries, rather than the 104 countries in the initial sample. The reason is that for ten countries (Gabon, Guyana, Kiribati, Lebanon, St. Lucia, Myanmar, Suriname, Syrian Arab Republic, Vanuatu and Zimbabwe) only a single observation on the Gini index is available over the entire sample period, which prevents us from computing its annual change. Although the restricted models do not include the change in the Gini index, and therefore can be estimated with the full sample, to ensure comparability of the results across models we opt for reporting estimates over the reduced sample of 94 countries for all models. Nevertheless, additional exercises show that the estimates of the restricted models over the full sample of 104 countries are very similar to those in Tables 6 and 7.

[23] The illustration in the text assumes changes of arbitrary magnitude in the values of the variables. Alternatively, we could have organized the discussion around 1-standard deviation changes of the variables. However, this would have resulted in unrealistically large changes when applied to the initial income conditions.

measure considered (0.69 for P0 and W, and above 0.80 for P1 and P2).[24] Hence, income and inequality, taken together, do an excellent job at explaining poverty club membership.

Comparing these pseudo-R2 with those obtained from the restricted models, we obtain a first idea about the relevance of each channel and dimension to position each country in the corresponding club. The first restricted model (9), which includes initial conditions only, yields a pseudo-R2 below 0.18 for all poverty measures, far behind the values obtained with the full model. The second restricted model, which includes income variables only, yields a pseudo-R2 of about 0.50 for all poverty measures, closer to, but still well below, those from the full model, with the gap being particularly large for P2. These simple comparisons suggest that, first, income and inequality changes contribute more than initial conditions to explaining club membership; second, income explains more than inequality; third, the contribution of inequality (relative to that of income) seems to be larger for P2 than for the other poverty measures.

A more direct way of assessing the contribution of the individual variables to the model's overall explanatory power is through the use of dominance statistics. They quantify the respective contribution of each variable to McFadden's pseudo-R2 (see Budescu 1993 and Grömping 2007).[25]

Table 8 reports the dominance statistics of the full model (8) for each of the four poverty measures. The dominance statistics of the individual regressors add up to the pseudo-R2 value. The table shows that initial income and annual income growth are consistently the most dominant factors. Their individual contributions are roughly similar to each other – they range between 0.25 and 0.39 depending on the poverty measure under consideration. Together, the two income-related variables contribute between 0.56 (in the case of the Watts index) and 0.69 (for the poverty gap) to the pseudo-R2. For P0, initial income plays the leading role, while for the other poverty measures income growth is the most dominant factor.

[24] McFadden's pseudo-R2 is defined as $1-[\log(L_{full})/\log(L_{null})]$, where $[\log(L_{full})$ is the log likelihood of the estimated model and $\log(L_{null})$ is the log likelihood of the model without covariates and only a set of intercepts. It captures the performance improvement of the estimated specification relative to the null model. Values close to 1 indicate a high predictive ability. However, pseudo-R2 are typically lower than their OLS counterparts (see, e.g., Smith and McKenna, 2013). According to McFadden, "its values tend to be considerably lower than those of the R2 index and should not be judged by the standards for a good fit in OLS. For example, values of 0.2 to 0.4 represent an excellent fit" (McFadden, 1977).

[25] Dominance statistics are based on the estimation of 2^K-1 models including all possible combinations of K independent variables. The dominance statistic of each independent variable is a weighted average of its marginal contribution to the pseudo-R2 in the models in which the variable is included. The statistics are obtained using the STATA module "domin" (Luchman, 2013).

In contrast, the contributions of initial inequality and its change over time are much smaller. Like with income, their magnitude is roughly constant across poverty measures: initial inequality contributes between 0.07 and 0.14 to the overall fit, while the change in inequality plays a more modest role, adding 0.02-0.03 to the pseudo-R2. Together, their combined contribution ranges from 0.09 (in the case of headcount poverty) to 0.17 (for the squared poverty gap).

4.3. Predicting club membership

The preceding discussion focused on the overall explanatory power of the empirical models (8)-(10). But their ability to correctly predict countries' membership in the different clubs is also of interest, as are the respective roles of income and inequality, as well as initial conditions and performance over time, in shaping the accuracy of such predictions.

To explore these issues, we first use the estimates of the ordered logit models (8)-(10) to compute, for each country and poverty measure, the probability of belonging to each club, given the country's characteristics (i.e., initial levels of income and Gini index, and their changes). Next, we take the highest of these club-specific probabilities as indicating the country's club membership predicted by the model. We compare these predictions with actual club membership, as derived from the Philips and Sul clustering procedure in Section 3. For each poverty measure, we compute the number and percentage of countries whose club membership is correctly/incorrectly predicted.

We follow this procedure for the full model (8) as well as the restricted specifications (9)-(10). Comparison between the predictive accuracy of the full and the initial conditions-only model provides information on the role of changes of income and inequality along the transition, over and above the role of initial conditions. Likewise, comparison between the predictive accuracy of the full model and the income-only model is informative about the contribution of the inequality dimension to predicting club membership.

Table 9 summarizes the predictive performance of the estimated models. The club membership predictions of the full model show a high degree of accuracy: they are correct for the vast majority of countries -- between 81 and 96 percent of the total, depending on the poverty measure under consideration. In turn, the income-only specification does fairly well too, with a success rate ranging from 70 to 85 percent, which suggests that income plays a bigger role than inequality in shaping club membership. The specification including only initial conditions is consistently less successful. Across poverty measures, headcount poverty is the one for which club membership predictions show the lowest level of accuracy – perhaps because there are four headcount poverty clubs, as opposed to three under the other poverty measures.

While Table 9 portrays the overall success of each model's club membership predictions, its breakdown by club is also of interest, as it may provide insights on how the roles of the different variables shaping club membership vary across clubs. Thus, we next examine the disaggregation by club of each one of the cells in Table 9. In other words, for each estimated model and each poverty club under each poverty measure, we compute the number and percentage of countries whose club membership is correctly/incorrectly predicted. This yields the so-called confusion matrices (Ting, 2011) comparing, for each club, actual membership with the membership prediction generated by the ordered logit model. In addition, we can identify the specific countries for which the restricted and the full-model predictions differ.

For each poverty club, Table 10 shows the confusion matrices for P0 and Table 11 for the rest of the poverty measures. The rows correspond to actual membership, and the columns to model predictions. The main diagonal shows the successes in the prediction of each model for each club, while the cells outside the main diagonal represent failed predictions. The percentages add up to 100 for each row.

Overall, from Tables 10 and 11 we can extract three main conclusions. First, membership in the lowest-poverty club (Club 4 for P0, and Club 3 for the other poverty measures) is well predicted by all models. In most cases, the percentage of successful predictions exceeds 90% (i.e., the lowest percentage is 86% for the full and income-only models for P0). Interestingly, the model featuring initial conditions only does nearly as well (even better, in the case of P0) in this regard as the full model. Thus, initial (favorable) income and inequality conditions suffice to predict with a high degree of accuracy which countries will wind up in a low-poverty club.

Second, membership in the highest-poverty club (Club 1 in all cases) is fairly well predicted by the income-only model. This is particularly the case for headcount poverty (for which the membership predictions of the income-only model are correct in 88 percent of the cases) and the poverty gap (80 percent), and less so for the squared poverty gap and the Watts index (69 percent successful predictions). This suggests that, on the whole, inequality has played only a modest role for countries winding up in the highest-poverty club. However, this does not mean that inequality is invariably unimportant for predicting membership in the highest-poverty club.[26]

In contrast, initial conditions play a secondary role when explaining countries' membership in the highest-poverty club. The exception is P0, for which the initial conditions-only model correctly predicts 76 percent of the Club 1 membership. For the other poverty measures, the success rate at predicting membership in Club 1 is 25 percent or less. In all cases, it is below the success rate of the income-only restricted model.

Indeed, several countries actually belonging to Club 1 under P0, which enjoyed relatively favorable initial conditions, are predicted by the initial conditions-only specification to wind up in Clubs 3 or 4, while the full model correctly places them in Club 1. Closer inspection reveals that these countries experienced large increases in the Gini index (or very small decreases) and decreases in their income levels between 1981 and 2015.[27]

Third, the various models generally have a harder time at predicting membership in intermediate-poverty clubs (Clubs 2 and 3 for P0, and Club 2 for P1, P2 and W). The initial conditions-only model does especially poorly in this regard: for P0, P1 and P2 its predictions of membership in these clubs are all incorrect. The conclusion is that initial conditions have been of relatively little consequence for countries belonging to intermediate-poverty clubs.[28]

The income-only model does better at predicting intermediate-club membership – but the success rate of its predictions is in most cases far below that of the full model. This underperformance is especially visible for P2, where the success rate of the income-only model at predicting membership in Club 2 is 43 p.p. lower than that of the full model. From this we can conclude that the inequality dimension plays a much more substantive role in determining

[26] Two relevant examples are those of Republic of Congo and Haiti, which the full-model prediction correctly places in Club 1, while the income-only model does not. The likely reason is that both countries exhibit initial inequality and/or inequality changes well above the sample medians.

[27] Some examples are Cote d'Ivoire, Guinea Bissau, Liberia, Nigeria, Togo, and Yemen.

[28] There are multiple examples of countries that the initial conditions-only model places in a high-poverty club, while the prediction of the full model correctly locates them in a lower-poverty intermediate club. This is the case, for example, of Indonesia, Guatemala, Mauritania, Namibia, Nepal and Pakistan. Under P0, all these countries belong in Club 3, but the initial conditions-only model places them in Club 1. The common thread is that, in spite of relatively adverse initial conditions, these countries were able to improve their position over time through sustained increases in income levels and, in most cases, reductions (or small increases) in inequality.

membership in intermediate-poverty clubs. This stands in contrast with membership in the highest-poverty clubs, for which inequality plays a limited role, as we saw above.[29]

5. CONCLUSIONS

In this paper we have analysed the dynamics of different dimensions of poverty using a large cross-country panel dataset comprising more than a hundred emerging and developing countries over more than three decades. Our framework allows not only for standard forms of poverty convergence across countries -- absolute and conditional convergence -- but also for club convergence, which has not been explored in the existing literature.

Using a panel clustering approach, we unambiguously reject absolute and conditional convergence. Instead, we find strong evidence of poverty convergence clubs: different groups of countries are converging to different long-run poverty levels. This applies to all the poverty measures we explore. Moreover, we also find that club membership is remarkably consistent across them.

The implication is that, to the dismay of the development community, the goal of global poverty eradication – which would require worldwide convergence of absolute poverty towards zero – may be at risk: between one-third and two-thirds of the countries in our sample (depending on the poverty measure under consideration) do not appear to be on the path towards zero poverty. Some of these countries – those that wound up in the highest-poverty clubs identified by our analysis – have seen their poverty rates remain at very high levels during the entire period of analysis. Other countries – those in intermediate-poverty clubs -- have achieved a substantial reduction in their poverty rates, but remain far from the zero-poverty goal. Only for the countries clustered into the lowest-poverty club that we identify do we find clear evidence that poverty is converging towards zero. This heterogeneity is consistent with the literature that, in general, has found no evidence of poverty convergence.

Convergence clubs are associated with the existence of multiple long-run poverty equilibria. Countries' long-run poverty rate depends not only on fundamental factors, but also on their

[29] Ignoring the inequality dimension makes the income-only model incur in systematic prediction errors regarding the club membership of intermediate-club countries. Some countries with very large initial levels and/or worsening inequality are optimistically predicted to belong to the lowest-poverty club (some examples under P0 are Guatemala, Honduras, Namibia and South Africa). The opposite happens to countries with low initial levels and/or improving inequality, which are pessimistically allocated to higher-poverty clubs (e.g., Angola, Ethiopia, Mauritania, Nepal, Pakistan, and the Philippines). In contrast, the full model, inclusive of inequality, predicts club membership correctly in these cases.

initial conditions (i.e., their initial levels of income and inequality). In contrast, under absolute or conditional convergence, initial conditions are irrelevant in the long run. Indeed, we find that initial conditions predict with a high degree of accuracy which countries end up belonging to a low-poverty club. Most of them start our period of analysis with a relatively favourable position (i.e., high income, and/or low inequality, and thus low poverty). In contrast, initial conditions play a secondary role in explaining countries' membership in the highest-poverty clubs, and are even less relevant for predicting the membership of intermediate-poverty clubs.

The paper goes one step further to asses the roles of income and inequality (measured by the Gini index) in the formation of poverty clubs. Overall, we find that income is the greatest driving force, in line with the existing literature. This is particularly true for the highest-poverty clubs, whose member countries experienced relatively low-income growth and/or started from low-income levels, and thus converge to a high-poverty equilibrium. However, this is not necessarily the case for the countries belonging to intermediate-poverty clubs. Income still plays the dominant role to account for their club membership, but inequality also matters, especially in the case of poverty severity.

To conclude, our results do not prompt optimism about the rapid eradication of global poverty. Many countries – certainly those trapped in the highest-poverty clubs, but possibly also many of those belonging to the intermediate-poverty clubs – appear to be falling behind.

While our framework has abstracted from policy levers, it naturally prompts the question of whether, and how, policies to achieve long-run poverty reduction should vary across poverty clubs. For example, one could conjecture that, for countries stuck in the highest-poverty clubs -- whose formation appears to be driven primarily by income rather than inequality -- raising income growth should be the top priority to exit the poverty trap. In turn, for countries converging towards lower-poverty equilibrium levels, such as those in the intermediate poverty clubs, a faster and more effective reduction of poverty could be achieved with inequality improvements complementing income growth.

6. REFERENCES

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. The Journal of Economic History, 46(2), 385-406.

Aguilar, R. A. C., Fujs, T. H., Jolliffe, D. M., Lakner, C., Mahler, D. G., Nguyen, M. C., and Yoshida, N. (2020). September 2020 PovcalNet Update: What's New (Nº. 14). The World Bank.

Apergis, N., and Payne, J. E. (2019). Convergence in condominium prices of major US metropolitan areas. International Journal of Housing Markets and Analysis.

Azariadis, C. and J. Stachurski (2005). Poverty Traps. In P. Aghion and S. Durlauf (eds.), Handbook of Economic Growth. Amsterdam: Elsevier.

Barro, R. J., and Sala-i-Martin, X. (1992). Convergence. Journal of Political Economy, 100(2), 223-251.

Bartkowska, M., and Riedl, A. (2012). Regional convergence clubs in Europe: Identification and conditioning factors. Economic Modelling, 29(1), 22-31.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: what the long-run data show. American Economic Review, 76(5), 1072-1085.

Bergstrom, K.A. (2020). The Role of Inequality for Poverty Reduction. Policy Research Working Paper 9409, World Bank, Washington DC.

Bernard, A. B., & Durlauf, S. N. (1996). Interpreting tests of the convergence hypothesis. Journal of Econometrics, 71(1-2), 161-173.

Bloom, D. E., Canning, D., and Sevilla, J. (2003). Geography and poverty traps. Journal of Economic Growth, 8(4), 355-378.

Bluhm, R., D. de Crombrugghe and A. Szirmai (2018). Poverty Accounting. European Economic Review 104 (C), 237–55.

Borsi, M. T., and Metiu, N. (2015). The evolution of economic convergence in the European Union. Empirical Economics, 48(2), 657-681.

Bourguignon, F. (2003). The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity across Countries and Time Periods. Inequality and Growth: Theory and Policy Implications. Working Paper 28104, WB, Washington DC.

Bowles, S., S.N. Durlauf and K.R. Hoff (2006). Poverty Traps. Princeton University Press.

Budescu, D. V. (1993). Dominance analysis: a new approach to the problem of relative importance of predictors in multiple regression. Psychological bulletin, 114(3), 542.

Cerra, V., B. Eichengreen, A. El-Ganainy and M. Schindler (2021). How to Achieve Inclusive Growth. Forthcoming. Oxford University Press and IMF.

Chen, S. and Ravallion, M. (2010). The developing world is poorer than we thought, but no less successful in the fight against poverty. The Quarterly Journal of Economics, 125(4), 1577-1625.

Cohen, J. (1960). A coefficient of agreement for nominal scales. Educational and psychological measurement, 20(1), 37-46.

Dollar, D., T. Kleineberg and A. Kraay (2016). Growth Still Is Good for the Poor. European

Economic Review 81, 68–85.

Dollar, D. and A. Kraay (2002). Growth is Good for the Poor. Journal of Economic Growth 7, 195-225.

Durlauf, S. N., and Johnson, P. A. (1995). Multiple regimes and cross-country growth behaviour. Journal of Applied Econometrics, 10(4), 365-384.

Easterly, W. (2006). The big push deja vu: a review of Jeffrey Sachs's the end of poverty: economic possibilities for our time. Journal of Economic Literature, 44(1), 96-105.

Ferreira, F.H.G., P.G. Leite and M. Ravallion (2010). Poverty Reduction without Economic Growth? Explaining Brazil's Poverty Dynamics, 1985–2004. Journal of Development Economics 93(1), 20–36.

Ferreira, F. H. (2012). Inequality of Opportunity Around the World: What Do We Know So Far?. World Bank-Inequality in Focus, 1(1), 8-11.

Ferreira, F.H.G., S. Chen, A. Dabalen, D. et al. (2016). A Global Count of the Extreme Poor in 2012: Data Issues, Methodology and Initial Results. The Journal of Economic Inequality 14(2), 141-172.

Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. Psychological bulletin, 76(5), 378.

Fosu, A. K. (2017). Growth, Inequality, and Poverty Reduction in Developing Countries: Recent Global Evidence. Research in Economics 71(2), 306–36.

Foster, J., Greer, J., and Thorbecke, E. (1984). A class of decomposable poverty measures. Econometrica, 761-766.

Galor, O. (1996). Convergence? Inferences from theoretical models. The economic journal, 106(437), 1056-1069.

Greene, W. H., and Hensher, D. A. (2010). Modeling ordered choices: A primer. Cambridge University Press.

Grömping, U. (2007). Estimators of relative importance in linear regression based on variance decomposition. The American Statistician, 61(2), 139-147.

Haider, L.J., W.J. Boonstra, G.D. Peterson and M. Schlüter (2018). Traps and Sustainable Development in Rural Areas: A Review. World Development 101, 311-321

Islam, N. (2003). What have we learnt from the convergence debate?. Journal of economic surveys, 17(3), 309-362.

Johnson, P., and Papageorgiou, C. (2020). What remains of cross-country convergence? Journal of Economic Literature, 58(1), 129-75.

Kalwij, A. and A. Verschoor (2007). Not by Growth Alone: The Role of the Distribution of Income in Regional Diversity in Poverty Reduction. European Economic Review 51(4), 805–29.

Kraay, A. (2006). When Is Growth Pro-Poor? Evidence from a Panel of Countries. Journal of Development Economics 80(1), 198–227.

Kremer, M., J. Willis and Y. Yang (2021). Converging to Convergence. NBER Chapters, in: NBER Macroeconomics Annual 2021, vol. 36, National Bureau of Economic Research, Inc.

Lakner, C., D. Gerszon Mahler, M. Negre and E. Beer Prydz (2020). How Much Does Reducing Inequality Matter for Global Poverty? Global Poverty Monitoring Technical Note 13, World Bank, Washington, DC.

Landis, J. R., and Koch, G. G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33, 159-174.

Lawrence, I., and Lin, K. (1989). A concordance correlation coefficient to evaluate reproducibility. Biometrics, 255-268.

Lopez, J. H., and Servén, L. (2006). A normal relationship?: poverty, growth, and inequality (Vol. 3814). World Bank Publications.

Luchman, J.N. (2013). DOMIN: Stata Module to Conduct Dominance Analysis. Statistical Software Components

McFadden, D. (1977). Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments (No. 474). Cowles Foundation for Research in Economics, Yale University.

McKelvey, R. D., and Zavoina, W. (1975). A statistical model for the analysis of ordinal level dependent variables. Journal of Mathematical Sociology, 4(1), 103-120.

Marrero, G.A. and L. Servén (2022). Poverty, Inequality and Growth: a Robust Relationship? Empirical Economics 63, 725-791.

Mookherjee, D., and Ray, D. (2001). Readings in the theory of economic development. Oxford: Blackwell Publishers.

Ouyang, Y., Shimeles, A. and E. Thorbecke (2019). Revisiting cross-country poverty convergence in the developing world with a special focus on Sub-Saharan Africa. World Development 117(375):13-28

Phillips, P. C., and Sul, D. (2007). Transition modelling and econometric convergence tests. Econometrica, 75(6), 1771-1855.

Phillips, P. C., and Sul, D. (2009). Economic transition and growth. Journal of applied econometrics, 24(7), 1153-1185.

Pinkovskiy, M and Sala-i-Martin, X. (2013). World Welfare is Rising: Estimation using Nonparametric Bounds on Welfare Measures. Journal of Public Economics, 97(C), 176-195.

Quah, D. T. (1993). Empirical Cross-section Dynamics in Economic Growth, European Economic Review 37, 426-434.

Quah, D. T. (1996). Twin peaks: growth and convergence in models of distribution dynamics. The economic journal, 106(437), 1045-1055.

Ravallion, M. (2004). Pro-Poor Growth: A Primer. Policy Research Working Paper 3242, WB.

Ravallion, M. (2005). A Poverty-Inequality Trade off? Journal of Economic Inequality 3, 169–181.

Ravallion, M. (2012). Why Don't we See Poverty Convergence? The American Economic Review 102(1), 504-523.

Ravn, M. O., and Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. Review of economics and statistics, 84(2), 371-376.

Sachs, J. D. (2006). The end of poverty: Economic possibilities for our time. New York: Penguin Press.

Sala-i-Martin, X. (2006). The World Distribution of Income: Falling Poverty and… Convergence, Period. The Quarterly Journal of Economics 121(2), 351-397.

Schnurbus, J., Haupt, H., and Meier, V. (2017). Economic transition and growth: a replication. Journal of Applied Econometrics, 32(5), 1039-1042.

Sen, A. (1976). Poverty: an ordinal approach to measurement. Econometrica: Journal of the Econometric Society, 219-231.

Smith, T. J., and McKenna, C. M. (2013). A comparison of logistic regression pseudo R2 indices. Multiple Linear Regression Viewpoints, 39(2), 17-26.

Solow, R. M. (1956). A contribution to the theory of economic growth. The quarterly journal of economics, 70(1), 65-94.

Ting K.M. (2011). Confusion Matrix. In: Sammut C., Webb G.I. (eds) Encyclopedia of Machine Learning. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-30164-8_157

Watts, H. W. (1968). "An Economic Definition of Poverty," in On Understanding Poverty, ed. by D. P. Moynihan. New York: Basic Books.

World Bank (2020). Poverty and shared prosperity 2020: reversals of fortune. World Bank Group.

TABLES

TABLE 1. ABSOLUTE POVERTY: DESCRIPTIVE STATISTICS

	Headcount (P0)			Poverty gap (P1)			Squared poverty gap (P2)			Watts (W)		
	1981	2015	Annual p.p. change	1981	2015	Annual p.p. change	1981	2015	Annual p.p. change	1981	2015	Annual p.p. change
mean	34.00	18.56	-0.45	15.50	6.92	-0.25	9.34	3.64	-0.17	25.25	10.25	-0.44
sd	29.11	21.49	-0.22	16.53	9.69	-0.20	11.55	5.80	-0.17	31.30	15.79	-0.46
p25	6.90	1.43	-0.16	1.69	0.40	-0.04	0.76	0.14	-0.02	2.26	0.53	-0.05
p50	25.11	7.74	-0.51	10.05	2.35	-0.23	5.20	0.93	-0.13	11.15	3.02	-0.24
p75	58.18	31.86	-0.77	26.09	10.64	-0.45	14.60	4.48	-0.30	39.95	13.27	-0.78

Note: The table reports descriptive statistics (mean, standard deviation and percentiles) for the four poverty measures at the beginning and the end of the sample period). p25 denotes the 25th percentile, p50 the median and p75 the 75th percentile. Poverty measures are expressed in percent, and annual changes in percentage points (p.p.).

TABLE 2. ABSOLUTE POVERTY: CONVERGENCE CLUBS

Measure	Club	Number of countries	b	t	β-converg.(*)	Absolute poverty rate (average) 1981	2015	Annual p.p. change
Headcount (P0)	Club1	26	-0.39	-1.57	-0.019	52.54	49.20	-0.10
	Club2	20	-0.15	-0.63	-0.022	38.44	22.94	-0.46
	Club3	20	-0.19	-0.48	-0.028	39.79	7.39	-0.95
	Club4	38	0.27	0.71	-0.029	15.93	1.18	-0.43
	Full sample	**104**	**-1.72**	**-27.51**	**-0.017**	**34.00**	**18.56**	**-0.45**
Poverty gap (P1)	Club1	22	-0.33	-1.56	-0.011	19.97	20.95	0.03
	Club2	15	0.38	1.01	-0.026	32.68	10.91	-0.64
	Club3	67	0.07	0.39	-0.028	10.19	1.42	-0.26
	Full sample	**104**	**-1.54**	**-24.96**	**-0.021**	**15.50**	**6.92**	**-0.25**
Squared poverty gap (P2)	Club1	17	0.02	0.05	-0.015	14.69	14.05	-0.02
	Club2	24	0.29	1.37	-0.028	15.28	4.48	-0.32
	Club3	63	2.20	4.09	-0.029	5.63	0.51	-0.15
	Full sample	**104**	**-1.38**	**-33.03**	**-0.023**	**9.34**	**3.64**	**-0.17**
Watts (W)	Club1	17	-0.14	-0.58	-0.015	39.83	37.29	-0.08
	Club2	34	-0.14	-0.98	-0.027	33.01	11.17	-0.64
	Club3	53	0.85	1.85	-0.029	15.59	0.99	-0.43
	Full sample	**104**	**-1.52**	**-15.75**	**-0.022**	**25.25**	**10.25**	**-0.44**

Note: For each poverty club under each poverty measure, the third column shows the number of member countries. The fourth and fifth columns show the b estimates and associated t-statistics from the log-t regression (Equation 5). The sixth column shows the β coefficients obtained from estimation of an absolute β-convergence regression. Finally, the last three columns report the average poverty rates (expressed in %) at the beginning and the end of the sample period, along with its annual change in p.p.
(*) All the β coefficients are significant at the 1% level.

TABLE 3. POVERTY CLUB MEMBERSHIP

Club	Headcount (P0)	Poverty gap (P1)	Squared poverty gap (P2)	Watts (W)
1	**Benin,** Burkina Faso, **Burundi, Central Afr. Rep., Congo Dem. Rep.,** Congo Rep., **Cote d'Ivoire,** Guinea, **Guinea-Bissau, Haiti, Kenya, Lesotho,** Liberia, **Madagascar, Malawi,** Mali, **Mozambique,** Niger, Nigeria, **Rwanda,** Sierra Leone, Tanzania, **Togo,** Yemen, **Zambia,** Zimbabwe.	**Benin, Burundi, Central Afr. Rep., Congo Dem. Rep.,** Congo Rep., **Cote d'Ivoire,** Djibouti, **Guinea-Bissau, Haiti, Kenya, Lesotho,** Liberia, **Madagascar, Malawi, Mozambique,** Nigeria, **Rwanda,** Suriname, **Togo,** Yemen, **Zambia,** Zimbabwe.	**Benin, Burundi, Central Afr. Rep., Congo Dem. Rep., Cote d'Ivoire,** Djibouti, **Guinea-Bissau, Haiti, Kenya, Lesotho, Madagascar, Malawi, Mozambique, Rwanda,** Suriname, **Togo, Zambia.**	**Benin, Burundi, Central Afr. Rep., Congo Dem. Rep., Cote d'Ivoire,** Djibouti, **Guinea-Bissau, Haiti, Kenya, Lesotho, Madagascar, Malawi, Mozambique, Rwanda, Togo, Zambia,** Zimbabwe.
2	**Angola,** Bangladesh, **Belize,** Botswana, **Cameroon, Chad, Comoros,** Djibouti, **Eswatini,** Ethiopia, Honduras, Kiribati, Lao People's, **Papua New Guinea, Senegal,** South Africa, Suriname, Syria, **Uganda,** Vanuatu.	**Angola, Belize,** Burkina Faso, **Cameroon, Chad, Comoros, Eswatini,** Guinea, Mali, Niger, **Papua New Guinea, Senegal,** Sierra Leone, Tanzania, **Uganda.**	**Angola, Belize,** Burkina Faso, **Cameroon, Chad, Comoros,** Congo Rep., **Eswatini,** Guinea, Honduras, Kiribati, Liberia, Mali, Niger, Nigeria, **Papua New Guinea, Senegal,** Sierra Leone, South Africa, Syria, Tanzania, **Uganda,** Yemen, Zimbabwe.	**Angola, Belize,** Bolivia, Botswana, Burkina Faso, **Cameroon, Chad,** Colombia, **Comoros,** Congo Rep., **Eswatini,** Ethiopia, Gabon, Ghana, Guinea, Honduras, India, Kiribati, Lao People's , Liberia, Mali, Niger, Nigeria, **Papua New Guinea,** Romania, **Senegal,** Sierra Leone, South Africa, Suriname, Syria, Tanzania, **Uganda,** Vanuatu, Yemen.
3 (3 and 4 for headcount)	Bolivia, **Cabo Verde,** Colombia, Gabon, **Gambia,** Ghana, **Guatemala, Guyana,** India, **Indonesia, Mauritania, Mexico, Myanmar, Namibia, Nepal, Pakistan, Peru, Philippines,** Romania, **Sudan.** **Algeria, Bhutan, Brazil, Bulgaria, Chile, China, Costa Rica, Czech Republic, Dominican Rep., Ecuador, Egypt, El Salvador, Fiji, Hungary, Iran, Iraq, Jamaica, Jordan, Korea, Lebanon, Malaysia, Mauritius, Mongolia, Morocco, Nicaragua, Panama, Paraguay, Poland, Seychelles, Sri Lanka, St. Lucia, Thailand, Tonga, Trinidad Tobago, Tunisia, Turkey, Uruguay, Vietnam.**	**Algeria,** Bangladesh, **Bhutan,** Bolivia, Botswana, **Brazil, Bulgaria, Cabo Verde, Chile, China,** Colombia, **Costa Rica, Czech Republic, Dominican Rep., Ecuador, Egypt, El Salvador,** Ethiopia, **Fiji,** Gabon, **Gambia,** Ghana, **Guatemala, Guyana,** Honduras, **Hungary,** India, **Indonesia, Iran, Iraq, Jamaica, Jordan,** Kiribati, **Korea,** Lao People's , **Lebanon, Malaysia, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Myanmar, Namibia, Nepal, Nicaragua, Pakistan, Panama, Paraguay, Peru, Philippines, Poland,** Romania, **Seychelles,** South Africa, **Sri Lanka, St. Lucia, Sudan,** Syria, **Thailand, Tonga, Trinidad Tobago, Tunisia, Turkey, Uruguay,** Vanuatu, **Vietnam.**	**Algeria,** Bangladesh, **Bhutan,** Bolivia, Botswana, **Brazil, Bulgaria, Cabo Verde, Chile, China,** Colombia, **Costa Rica, Czech Republic, Dominican Rep., Ecuador, Egypt, El Salvador,** Ethiopia, **Fiji,** Gabon, **Gambia,** Ghana, **Guatemala, Guyana, Hungary,** India, **Indonesia, Iran, Iraq, Jamaica, Jordan, Korea,** Lao People's , **Lebanon, Malaysia, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Myanmar, Namibia, Nepal, Nicaragua, Pakistan, Panama, Paraguay, Peru, Philippines, Poland,** Romania, **Seychelles, Sri Lanka, St. Lucia, Sudan, Thailand, Tonga, Trinidad Tobago, Tunisia, Turkey, Uruguay,** Vanuatu, **Vietnam.**	**Algeria,** Bangladesh, **Bhutan, Brazil, Bulgaria, Cabo Verde, Chile, China, Costa Rica, Czech Republic, Dominican Rep., Ecuador, Egypt, El Salvador, Fiji, Gambia, Guatemala, Guyana, Hungary, Indonesia, Iran, Iraq, Jamaica, Jordan, Korea, Lebanon, Malaysia, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Myanmar, Namibia, Nepal, Nicaragua, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Seychelles, Sri Lanka, St. Lucia, Sudan, Thailand, Tonga, Trinidad Tobago, Tunisia, Turkey, Uruguay, Vietnam.**

Note: The table shows the list of countries belonging to each of the estimated poverty clubs under each poverty measure. Countries in bold belong to the same club under all poverty measures.

TABLE 4. CONCORDANCE BETWEEN CONVERGENCE CLUBS OF DIFFERENT POVERTY MEASURES

	Headcount			Poverty gap			Squared poverty gap			Watts		
	Spearman correlation	Kappa	Concord. correlation	Spearman correlation	Kappa	Concord. correlation	Spearman correlation	Kappa	Concord. correlation	Spearman correlation	Kappa	Concord. correlation
Headcount	1	1	1	0.895	0.708	0.883	0.917	0.700	0.867	0.884	0.717	0.863
Poverty gap	--	--	--	1	1	1	0.936	0.840	0.930	0.835	0.690	0.851
Squared poverty gap	--	--	--	--	--	--	1	1	1	0.881	0.804	0.898
Watts	--	--	--	--	--	--	--	--	--	1	1	1

Note: The table shows the concordance between the memberships of the estimated poverty clubs obtained under the different poverty measures. Concordance is measured using three statistics: the Spearman rank correlation, the Kappa statistic (Cohen 1960) and the concordance correlation coefficient (Lin 1989).

TABLE 5. INCOME AND INEQUALITY: DESCRIPTIVE STATISTICS BY CLUB

		Income 1981		Income 2015		Gini (circa 1981)		Gini (circa 2015)		Annual income growth (%)		Annual Gini change (p.p)	
		mean	sd	mean	sd	mean	sd	Mean	sd	mean	sd	mean	sd
Headcount (P0)	Club 1	3.42	2.4	2.88	0.89	46.57	9.17	43.48	7.99	-0.03	1.66	-0.20	0.51
	Club 2	4.64	2.69	5.61	2.57	46.32	10.6	44.37	8.21	0.84	1.48	-0.24	0.54
	Club 3	5.44	4.2	8.29	3.29	42.62	10.13	41.52	6.97	1.90	1.53	-0.11	0.34
	Club 4	8.97	5.33	16.46	7.64	39.88	10.57	38.86	6.58	2.12	1.72	-0.05	0.31
Poverty gap (P1)	Club 1	4.43	2.77	3.39	2	47.8	9.61	46.55	7.28	-0.57	1.30	-0.07	0.49
	Club 2	2.94	2.33	4.03	1.9	47.6	7.97	40.94	6.4	1.43	1.54	-0.51	0.52
	Club 3	7.31	5.03	12.59	7.57	40.89	10.51	40.1	7.34	1.87	1.65	-0.06	0.31
Squared poverty gap (P2)	Club 1	4.16	2.88	3.28	2.21	50.06	9.54	48.19	6.9	-0.48	1.25	-0.10	0.52
	Club 2	4.02	2.62	4.47	2.28	45.91	8.47	41.85	7.54	0.72	1.75	-0.36	0.52
	Club 3	7.36	5.17	12.94	7.64	40.51	10.4	39.71	6.84	1.99	1.61	-0.06	0.31
Watts (W)	Club 1	4.04	2.69	2.96	1.18	49.21	9.47	47.34	6.55	-0.56	1.23	-0.10	0.52
	Club 2	4.56	3.17	5.65	3.43	44.45	9.56	42.21	7.71	0.92	1.55	-0.24	0.50
	Club 3	7.69	5.34	13.89	7.81	40.7	10.55	39.34	6.86	2.13	1.66	-0.08	0.32
Full sample		**6.07**	**4.64**	**9.41**	**7.52**	**43.32**	**10.44**	**41.59**	**7.59**	**1.29**	**1.84**	**-0.13**	**0.42**

Note: The table shows, for each poverty club under each poverty measure, the average levels of income (expressed in 2011 PPP-adjusted USD per day) and the Gini index (in percentage) at the beginning and end of the sample period, along with their annual growth (annual change in p.p. for the Gini index) over the sample period.

TABLE 6. ORDERED LOGIT MODEL ESTIMATION RESULTS. HEADCOUNT

	Full model	Restricted model (only initial conditions)	Restricted model (only income)
Initial income (log)	0.09***	0.02***	0.05***
	(-0.01)	(0.00)	(-0.01)
Annual income growth	3.60***		2.25***
	(-0.63)		(-0.33)
Initial Gini index	-0.28***	-0.07***	
	(-0.06)	(-0.02)	
Annual Gini index change	-3.47***		
	(-1.1)		
$\boldsymbol{\mu_1}$	-0.15	-2.18**	6.90***
	(-1.61)	(-0.97)	(-1.00)
$\boldsymbol{\mu_2}$	4.50**	-1.17	9.72***
	(-1.87)	(-0.95)	(-1.45)
$\boldsymbol{\mu_3}$	8.58***	-0.1	12.17***
	(-2.12)	(-0.94)	(-1.72)
N	94	94	94
Pseudo R2	0.69	0.17	0.54

Note: The table shows the estimated results of the ordered logit models expressed in Equations (8)-(10) for headcount poverty. The full model includes initial income, initial Gini index, average income growth and average Gini change. The first restricted model includes only initial income and the initial Gini index, and the second includes only initial income and its average growth rate. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 7. ORDERED LOGIT MODEL ESTIMATION RESULTS. POVERTY GAP, SQUARED POVERTY GAP AND WATTS

	Poverty gap (P1)			Squared poverty gap (P2)			Watts (W)		
	Full model	**Restricted model (only initial conditions)**	**Restricted model (only income)**	**Full model**	**Restricted model (only initial conditions)**	**Restricted model (only income)**	**Full model**	**Restricted model (only initial conditions)**	**Restricted model (only income)**
Initial income (log)	0.11***	0.01***	0.05***	0.11***	0.01***	0.04***	0.06***	0.01***	0.03***
	(-0.03)	(0.00)	(-0.01)	(-0.03)	(0.00)	(-0.01)	(-0.01)	(0.00)	(-0.01)
Annual income growth	5.23***		2.62***	4.99***		2.00***	2.81***		1.80***
	(-1.29)		(-0.47)	(-1.22)		(-0.35)	(-0.53)		(-0.31)
Initial Gini index	-0.44***	-0.07***		-0.54***	-0.09***		-0.26***	-0.07***	
	(-0.13)	(-0.02)		(-0.14)	(-0.03)		(-0.06)	(-0.02)	
Annual Gini index change	-4.58***			-5.08***			-4.58***		
	(-1.56)			(-1.65)			(-1.31)		
μ_1	-5.36*	-3.19***	6.26***	-11.5***	-4.34***	4.22***	-5.14**	-3.42***	3.55***
	(-2.95)	(-1.12)	(-1.32)	(-3.84)	(-1.16)	(-0.97)	(-2.05)	(-1.05)	(-0.83)
μ_2	0.13	-2.21***	9.08***	-4.29	-2.84**	7.35***	1.12	-1.57*	7.33***
	(-2.9)	(-1.09)	(-1.7)	(-3.17)	(-1.1)	(-1.33)	(-1.98)	(-0.99)	(-1.26)
N	94	94	94	94	94	94	94	94	94
Pseudo-R2	0.81	0.14	0.61	0.83	0.17	0.52	0.67	0.14	0.48

Note: The table shows the estimated results of the ordered logit models in Equations (8)-(10) for the poverty gap, squared poverty gap and the Watts index. The full model includes initial income, initial Gini index, average income growth and average Gini change. The first restricted model includes only initial income and the initial Gini index, and the second includes only initial income and its average growth rate. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE 8. DOMINANCE STATISTICS OF THE FULL MODEL

	Headcount (P0)	Poverty gap (P1)	Squared poverty gap (P2)	Watts (W)
Initial income (log)	0.33	0.30	0.29	0.25
Annual income growth	0.28	0.39	0.36	0.31
Initial Gini index	0.07	0.09	0.14	0.09
Gini index change	0.02	0.03	0.03	0.03
Pseudo-R2	**0.69**	**0.81**	**0.83**	**0.67**

Note: The table reports the dominance statistics of the full model in Equation (8), including initial income, initial Gini index, average income growth and average Gini change. . The dominance statistics quantify the respective contribution of each variable to McFadden's pseudo-R2.

TABLE 9. CONFUSION MATRICES: PREDICTIVE ACCURACY OF THE ESTIMATED ORDERED LOGIT MODELS

	Headcount (P0)	Poverty Gap (P1)	Squared poverty gap (P2)	Watts (W)
Full model	81% (76)	93% (87)	96% (90)	87% (82)
Restricted model (only initial conditions)	56% (53)	66% (62)	61% (57)	57% (54)
Restricted model (only income)	70% (66)	85% (80)	80% (75)	72% (68)

Note: The table reports the overall predictive performance of the ordered logit models in Equations (8)-(10) for each of the four poverty measures. The predictive performance is expressed as the percentage and number (in parentheses) of countries correctly predicted – i.e., those for which the club membership predicted by the model under consideration matches their actual club membership as obtained using Phillip and Sul's (2007) methodology. The full model includes initial income, initial Gini index, average income growth and average Gini change. The first restricted model includes only initial income and the initial Gini index, and the second includes only initial income and its average growth rate.

TABLE 10. CONFUSION MATRICES BY CLUB. HEADCOUNT

Full model vs actual membership

Actual membership	Full model Club 1	Club 2	Club 3	Club 4	Total
Club 1	**92% (23)**	8% (2)	0% (0)	0% (0)	100% (25)
Club 2	13% (2)	**75% (12)**	13% (2)	0% (0)	100% (16)
Club 3	0% (0)	12% (2)	**59% (10)**	29% (5)	100% (17)
Club 4	0% (0)	0% (0)	14% (5)	**86% (31)**	100% (36)

Restricted model (only initial conditions) vs actual membership

Actual membership	Initial conditions only Club 1	Club 2	Club 3	Club 4	Total
Club 1	**76% (19)**	0% (0)	0% (0)	24% (6)	100% (25)
Club 2	50% (8)	**0% (0)**	0% (0)	50% (8)	100% (16)
Club 3	41% (7)	0% (0)	**0% (0)**	59% (10)	100% (17)
Club 4	6% (2)	0% (0)	0% (0)	**94% (34)**	100% (36)

Restricted model (only income) vs actual membership

Actual membership	Income only Club 1	Club 2	Club 3	Club 4	Total
Club 1	**88% (22)**	12% (3)	0% (0)	0% (0)	100% (25)
Club 2	25% (4)	**50% (8)**	6% (1)	19% (3)	100% (16)
Club 3	0% (0)	35% (6)	**29% (5)**	35% (6)	100% (17)
Club 4	0% (0)	3% (1)	11% (4)	**86% (31)**	100% (36)

Note: The confusion matrix reports the predictive performance for each club of the ordered logit models in Equations (8)-(10) for headcount poverty. The full model includes initial income, initial Gini index, average income growth and average Gini change. The first restricted model includes only initial income and the initial Gini index, and the second includes only initial income and its average growth rate. The predictive performance is expressed as the percentage and number (in parentheses) of countries correctly predicted – i.e., those for which the club membership predicted by the model under consideration matches their actual club membership as obtained using Phillip and Sul's (2007) methodology. The rows correspond to actual membership, and the columns to model predictions. The main diagonal (in bold) shows the successful predictions of each model for each club, while the cells outside the main diagonal represent failed predictions. The percentages add up to 100 for each row.

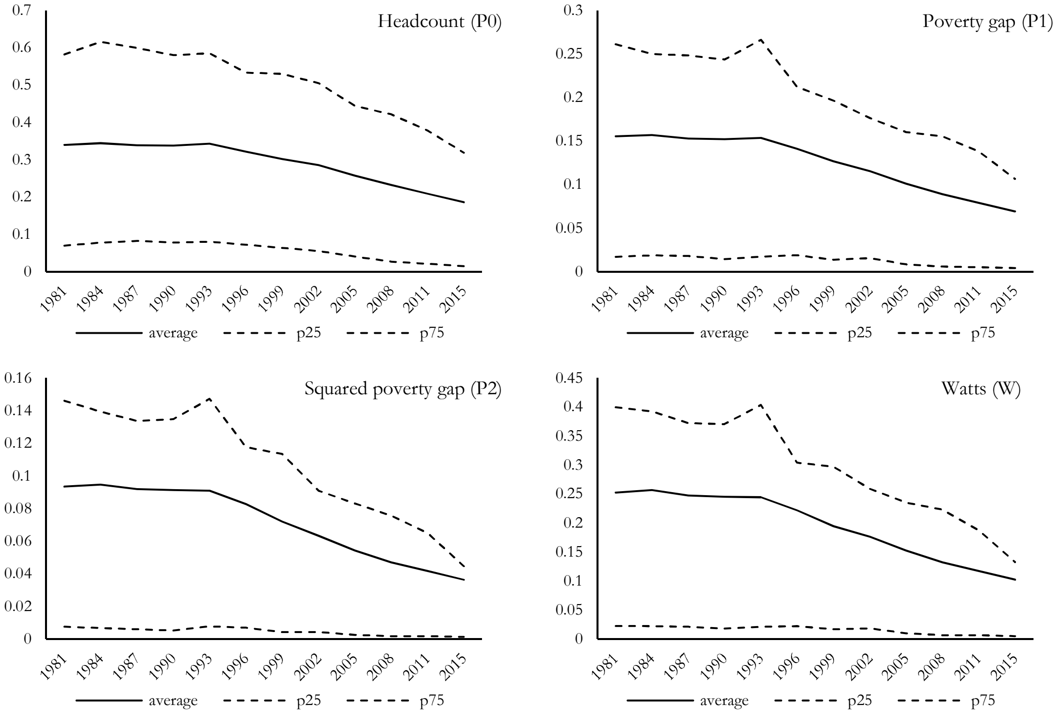
TABLE 11. CONFUSION MATRICES BY CLUB. POVERTY GAP, SQUARED POVERTY GAP AND WATTS

Full model vs **Actual membership**					
			Full model		
Actual membership		**Club 1**	**Club 2**	**Club 3**	**Total**
	Club 1	**90% (18)**	10% (2)	0% (0)	100% (20)
Poverty gap (P1)	**Club 2**	7% (1)	**80% (12)**	13% (2)	100% (15)
	Club 3	0% (0)	3% (2)	**97% (57)**	100% (59)
	Club 1	**94% (15)**	6% (1)	0% (0)	100% (16)
Squared poverty gap (P2)	**Club 2**	0% (0)	**95% (20)**	5% (1)	100% (21)
	Club 3	0% (0)	4% (2)	**96% (55)**	100% (57)
	Club 1	**94% (15)**	6% (1)	0% (0)	100% (16)
Watts (W)	**Club 2**	3% (1)	**79% (23)**	17% (5)	100% (29)
	Club 3	0% (0)	10% (5)	**90% (44)**	100% (49)
Restricted model (only initial conditions) vs **Actual membership**					
			Initial conditions only		
Actual membership		**Club 1**	**Club 2**	**Club 3**	**Total**
	Club 1	**25% (5)**	0% (0)	75% (15)	100% (20)
Poverty gap (P1)	**Club 2**	33% (5)	**0% (0)**	67% (10)	100% (15)
	Club 3	3% (2)	0% (0)	**97% (57)**	100% (59)
	Club 1	**25% (4)**	19% (3)	56% (9)	100% (16)
Squared poverty gap (P2)	**Club 2**	24% (5)	**0% (0)**	76% (16)	100% (21)
	Club 3	2% (1)	5% (3)	**93% (53)**	100% (57)
	Club 1	**19% (3)**	50% (8)	31% (5)	100% (16)
Watts (W)	**Club 2**	14% (4)	**28% (8)**	59% (17)	100% (29)
	Club 3	0% (0)	12% (6)	**88% (43)**	100% (49)
Restricted model (only income) vs **Actual membership**					
			Income only		
Actual membership		**Club 1**	**Club 2**	**Club 3**	**Total**
	Club 1	**80% (16)**	20% (4)	0% (0)	100% (20)
Poverty gap (P1)	**Club 2**	13% (2)	**53% (8)**	33% (5)	100% (15)
	Club 3	2% (1)	3% (2)	**95% (56)**	100% (59)
	Club 1	**69% (11)**	31% (5)	0% (0)	100% (16)
Squared poverty gap (P2)	**Club 2**	24% (5)	**52% (11)**	24% (5)	100% (21)
	Club 3	0% (0)	7% (4)	**93% (53)**	100% (57)
	Club 1	**69% (11)**	31% (5)	0% (0)	100% (16)
Watts (W)	**Club 2**	17% (5)	**52% (15)**	31% (9)	100% (29)
	Club 3	0% (0)	14% (7)	**86% (42)**	100% (49)

Note: This confusion matrix reports the predictive performance for each club of the ordered logit models in Equations (8)-(10) for the poverty gap, squared poverty gap and the Watts index. The full model includes initial income, initial Gini index, average income growth and average Gini change. The first restricted model includes only initial income and the initial Gini index, and the second includes only initial income and its average growth rate. The predictive performance is expressed as the percentage and number (in parentheses) of countries correctly predicted – i.e., those for which the club membership predicted by the model under consideration matches their actual club membership as obtained using Phillip and Sul's (2007) methodology. The rows correspond to actual membership, and the columns to model predictions. The main diagonal (in bold) shows the successful predictions of each model for each club, while the cells outside the main diagonal represent failed predictions. The percentages add up to 100 for each row.

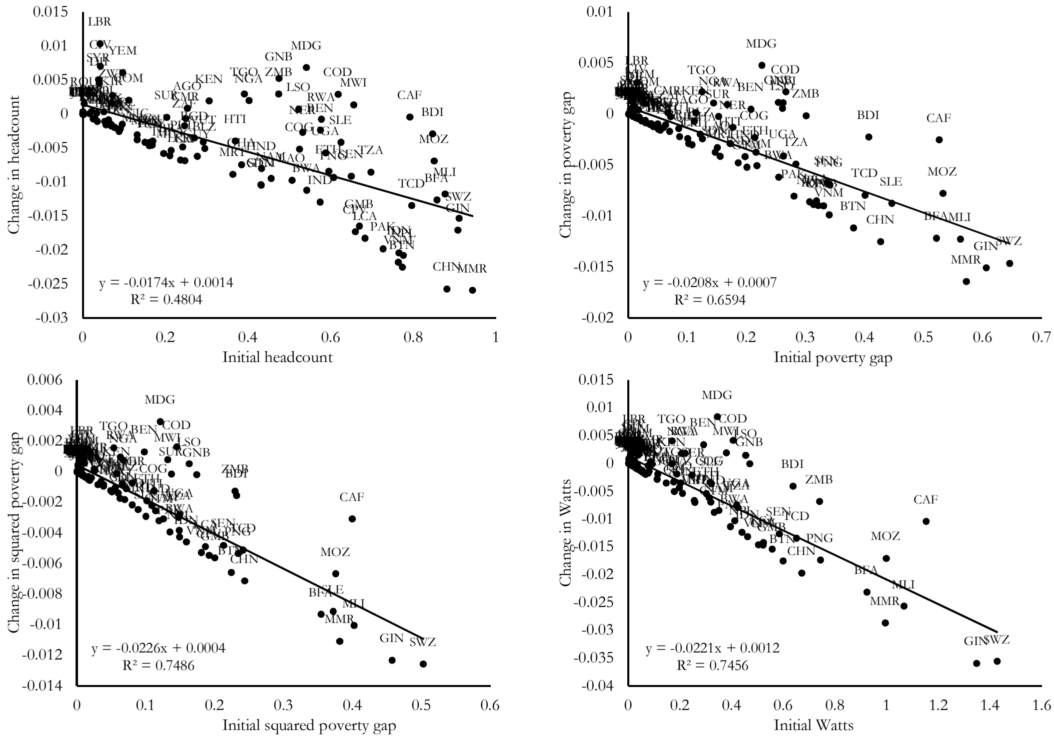
FIGURES

FIGURE 1. ABSOLUTE POVERTY TRENDS



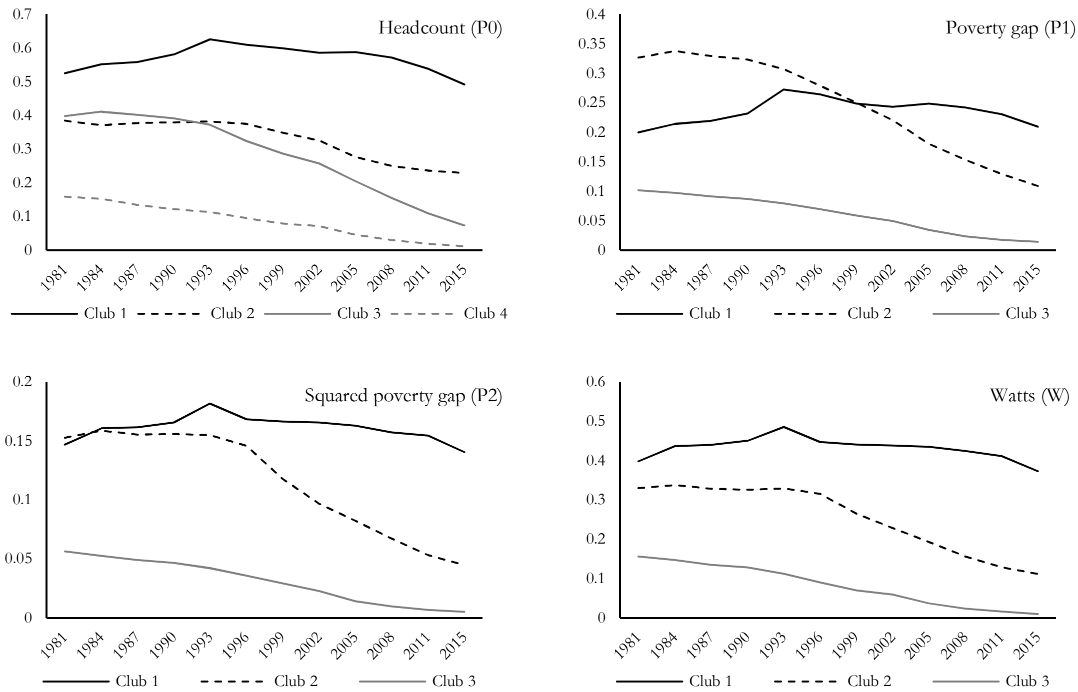
Note: The figures show the time path of the cross-sectional average and 25th and 75th percentiles of each poverty measure for the sample of 104 developing countries over the period 1981-2015.

FIGURE 2. ABSOLUTE POVERTY. BETA CONVERGENCE



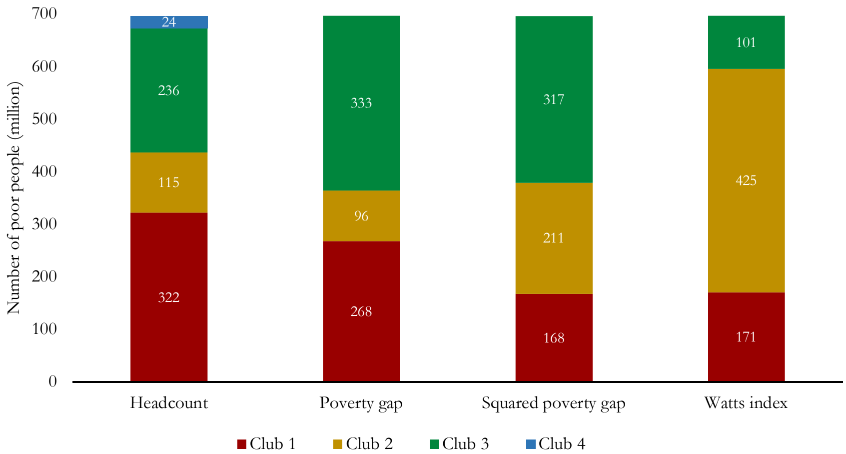
Note: The figures show, for the sample of 104 developing countries, standard β-convergence graphs for the different poverty measures, that is, the relationship between the annual change in poverty (in p.p.) between 1981 and 2015 and its initial level (in 1981).

FIGURE 3. ABSOLUTE POVERTY TRENDS BY CONVERGENCE CLUB



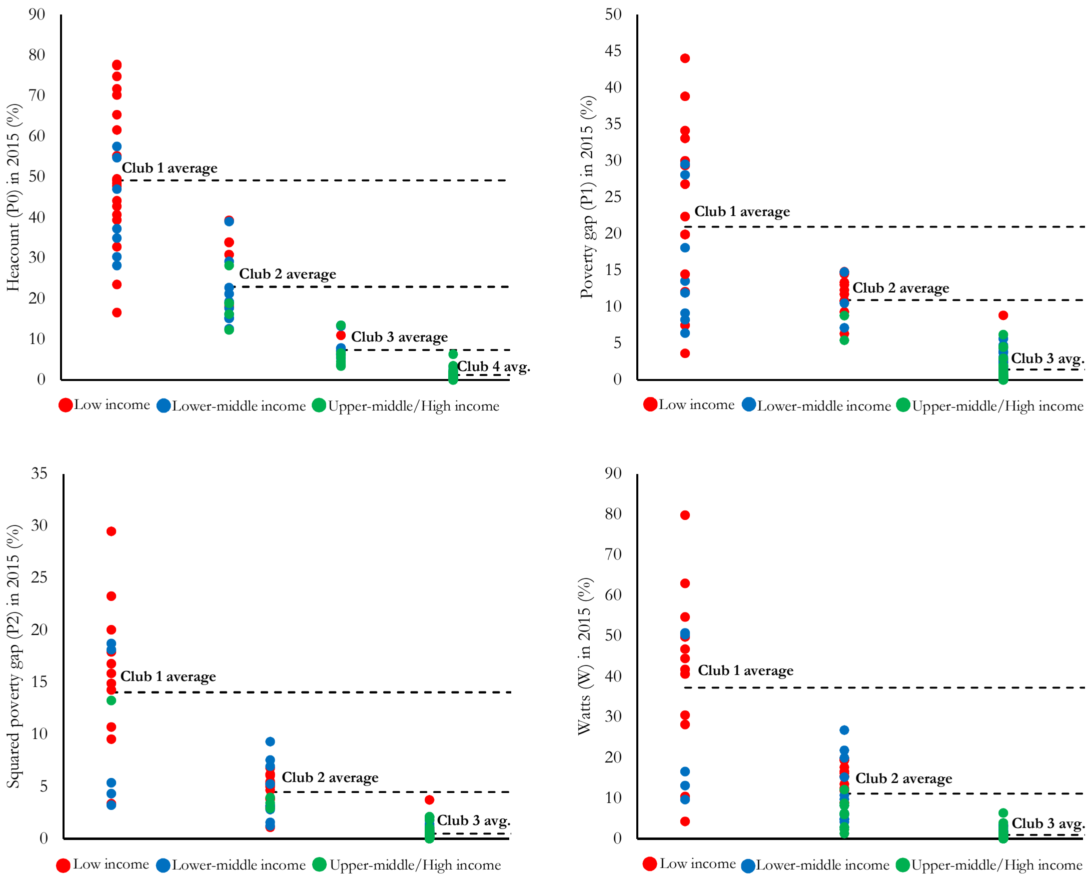
Note: The figures show the time path of the of the of the cross-sectional average of each poverty measure for each poverty club between 1981 and 2015.

FIGURE 4. TOTAL NUMBER OF POOR IN 2015, BY POVERTY CLUB



Note: The figure shows how the world's poor were allocated in 2015 across poverty clubs. For each country, we multiply its headcount poverty rate by its 2015 population. The totals by club are calculated summing the number of poor over the countries belonging to each club under the corresponding poverty measure.

FIGURE 5. POVERTY CLUBS, WORLD BANK'S INCOME GROUPS AND POVERTY LEVELS IN 2015



Note: In the figures, the vertical axis measures the 2015 poverty rate of each country, with countries grouped by poverty club along the horizontal axis. The colors denote the classification of each country according to the World Bank income classification for 2015.

APPENDIX A. ABSOLUTE POVERTY MEASURES

TABLE A1. ABSOLUTE POVERTY MEASURES: INITIAL AND FINAL PERIOD

Reg.	Country	ISO3	1981 P0	1981 P1	1981 P2	1981 W	2015 P0	2015 P1	2015 P2	2015 W	Population (2015, million)
MENA	Algeria	DZA	2.67	0.19	0.02	0.24	0.36	0.13	0.11	0.11	39.87
SSA	Angola	AGO	25.28	11.11	6.57	18.57	28.2	8.78	3.95	12.11	27.86
SA	Bangladesh	BGD	27.04	6.24	2.06	7.87	15.16	2.75	0.78	3.29	161.20
LAC	Belize	BLZ	29.47	12.08	7.12	20.1	12.3	5.42	3.42	8.15	0.36
SSA	Benin	BEN	57.48	20.72	9.79	29.01	49.52	22.36	14.26	40.6	10.58
SA	Bhutan	BTN	77.26	38.07	22.37	59.73	0.85	0.13	0.04	0.16	0.79
LAC	Bolivia	BOL	5.08	0.64	0.12	0.71	6.35	2.81	1.74	4.88	10.72
SSA	Botswana	BWA	54.12	25.39	14.85	41.01	16.19	4.47	1.84	5.97	2.21
LAC	Brazil	BRA	21.39	8.63	5.06	11.02	3.38	1.17	0.61	1.48	205.96
ECA	Bulgaria	BGR	0.06	0.06	0.06	0	1.25	0.45	0.31	1.05	7.18
SSA	Burkina Faso	BFA	85.62	52.11	35.39	92.12	42.8	10.78	3.77	13.48	18.11
SSA	Burundi	BDI	84.62	40.65	23.14	63.57	74.84	33.05	17.9	49.72	10.20
SSA	Cabo Verde	CPV	65.88	32.08	19.17	52.02	7.21	1.66	0.61	2.14	0.53
SSA	Cameroon	CMR	24.94	6.63	2.51	8.48	22.76	7.11	3.13	9.69	22.83
SSA	Central African	CAF	79.09	52.57	39.93	115.13	77.74	44.01	29.47	79.74	4.55
SSA	Chad	TCD	79.52	40	24.11	64.89	33.85	13.03	6.75	19.3	14.01
LAC	Chile	CHL	7.75	2.84	1.63	4.26	1.3	0.76	0.61	0.84	17.76
EAP	China	CHN	88.07	42.67	24.31	67.03	0.73	0.16	0.07	0.17	1371.22
LAC	Colombia	COL	9.56	4.92	3.85	3.27	4.54	1.75	1.05	2.3	48.23
SSA	Comoros	COM	11.09	2.79	1.07	3.7	18.1	6.33	3	8.97	0.78
SSA	Congo, Dem.	COD	61.74	26.61	14.48	40.49	71.74	34.12	20.02	54.65	76.20
SSA	Congo, Rep.	COG	52.43	21.35	11.15	31.51	34.94	13.53	6.95	19.93	5.00
LAC	Costa Rica	CRI	24.7	10.76	6.23	17.67	1.52	0.59	0.37	0.69	4.81
SSA	Cote d'Ivoire	CIV	4.27	1.35	0.79	2.35	28.21	9.13	4.3	13.07	23.11
ECA	Czech Republic	CZE	0.02	0.01	0.01	0	0	0	0	0	10.55
MENA	Djibouti	DJI	3.92	0.96	0.39	1.27	19.31	6.41	3.2	9.64	0.93
LAC	Dominican R.	DOM	5.28	1.73	0.9	2.09	1.78	0.45	0.19	0.66	10.53
LAC	Ecuador	ECU	16.89	6.96	3.85	11.02	3.44	1.23	0.67	1.59	16.14
MENA	Egypt	EGY	16.77	3.02	0.83	3.57	1.35	0.16	0.04	0.19	93.78
LAC	El Salvador	SLV	16.05	10.13	10	5.4	1.93	0.4	0.13	0.5	6.31
SSA	Eswatini	SWZ	90.98	64.46	50.24	142.61	38.99	14.78	7.55	21.8	1.32
SSA	Ethiopia	ETH	59.46	21.52	10.14	30.13	30.9	8.84	3.72	11.82	99.87
EAP	Fiji	FJI	7.7	1.58	0.5	1.93	0.96	0.16	0.04	0.18	0.89
SSA	Gabon	GAB	3.37	0.74	0.27	0.96	3.96	0.96	0.37	1.26	1.93
SSA	Gambia, The	GMB	66.84	32.98	20	55.48	10.98	2.5	0.89	3.18	1.98
SSA	Ghana	GHA	38.37	12.47	5.54	17.37	13.19	4.32	2.08	6.29	27.58
LAC	Guatemala	GTM	43.07	20	11.88	33.08	7.88	2.31	1.05	3.19	16.25
SSA	Guinea	GIN	90.73	60.53	45.7	134.58	32.82	9.3	3.86	12.45	12.09
SSA	Guinea-Bissau	GNB	47.43	25.36	17.39	46.83	65.34	29.36	16.76	46.74	1.77
LAC	Guyana	GUY	27.67	9.98	4.87	14.54	6.63	1.93	0.76	2.67	0.77
LAC	Haiti	HTI	36.88	17.18	10.85	31.15	23.48	7.46	3.36	10.37	10.71
LAC	Honduras	HND	43.18	19.71	11.41	31.74	16.16	5.64	2.79	8.16	8.96
ECA	Hungary	HUN	0.06	0.06	0.06	0	0.49	0.3	0.2	0.54	9.84
SA	India	IND	57.41	18.54	7.99	25.4	13.42	2.38	0.65	2.82	1309.05
EAP	Indonesia	IDN	76.43	31.32	15.87	46.02	7.18	1.19	0.31	1.38	258.16
MENA	Iran	IRN	8.78	2.18	0.81	2.81	0.26	0.04	0.01	0.04	79.36
MENA	Iraq	IRQ	6.36	1.12	0.32	1.34	2.39	0.36	0.09	0.41	36.12
LAC	Jamaica	JAM	6.92	1.89	0.87	2.22	1.84	0.43	0.14	0.53	2.87
MENA	Jordan	JOR	0	0	0	0	0.2	0.04	0.01	0.04	9.16
SSA	Kenya	KEN	30.56	11.35	5.75	16.72	37.29	11.91	5.36	16.55	47.24
EAP	Kiribati	KIR	7.02	1.66	0.64	2.17	12.58	3.14	1.23	4.14	0.11
EAP	Korea, Rep.	KOR	2.5	0.84	0.47	1.43	0.25	0.11	0.05	0.14	51.01
EAP	Lao People's	LAO	50.6	15.01	5.97	19.59	17.66	3.86	1.25	4.75	6.66
MENA	Lebanon	LBN	0.07	0.01	0	0.02	0	0	0	0	5.85
SSA	Lesotho	LSO	52.22	26.04	16.28	45.28	54.78	28.07	18.1	50.24	2.17
SSA	Liberia	LBR	4.17	1.46	0.77	2.3	39.44	12.1	5.11	16.2	4.50
SSA	Madagascar	MDG	54.09	22.55	12.06	34.34	77.47	38.82	23.25	62.94	24.23
SSA	Malawi	MWI	65.53	26.14	13.15	37.85	70.21	29.98	15.85	44.42	17.57

EAP	Malaysia	MYS	3.51	0.72	0.25	0.9	0.01	0	0	0	30.72
SSA	Mali	MLI	87.61	56.13	40.19	106.55	47.75	14.5	6.04	19.35	17.47
SSA	Mauritania	MRT	36.28	15.47	8.88	25.61	6.25	1.49	0.54	1.89	4.18
SSA	Mauritius	MUS	21.02	5.01	1.84	6.43	0.34	0.06	0.02	0.07	1.26
LAC	Mexico	MEX	6.18	1.74	0.74	2.41	3.37	0.82	0.32	1.07	125.89
EAP	Mongolia	MNG	13.14	2.83	0.9	3.4	0.32	0.04	0.01	0.04	2.98
MENA	Morocco	MAR	15	3.62	1.19	4.68	0.92	0.16	0.05	0.2	34.80
SSA	Mozambique	MOZ	84.99	53.19	37.54	99.69	61.61	26.79	14.9	41.7	28.01
EAP	Myanmar	MMR	94.23	57.18	38.13	99.26	6.22	1.45	0.51	1.82	52.40
SSA	Namibia	NAM	45.55	21.69	12.52	34.91	13.44	4.53	2.1	6.32	2.43
SA	Nepal	NPL	77.53	30.61	14.88	43.78	7.03	1.39	0.43	1.7	28.66
LAC	Nicaragua	NIC	13.17	3.78	1.65	5.2	2.9	0.64	0.24	0.82	6.08
SSA	Niger	NER	53.16	17.66	7.99	24.56	44.16	13.35	5.49	17.65	19.90
SSA	Nigeria	NGA	40.19	14.35	6.73	20.52	47	18.11	9.3	26.74	181.18
SA	Pakistan	PAK	72.61	27.99	13.49	39.42	5.33	0.71	0.15	0.8	189.38
LAC	Panama	PAN	9.06	4.07	3.04	4.09	1.98	0.53	0.24	0.58	3.97
EAP	Papua New Gu.	PNG	60.71	34.03	23.36	74.15	29.17	10.5	5.23	15.16	7.92
LAC	Paraguay	PRY	1.6	0.37	0.19	0.36	1.89	0.41	0.14	0.5	6.64
LAC	Peru	PER	2.17	0.53	0.22	0.75	3.55	0.97	0.41	1.31	31.38
EAP	Philippines	PHL	24.16	5.87	1.89	7.49	7.81	1.45	0.42	1.73	101.72
ECA	Poland	POL	0.2	0.14	0.14	0.02	0	0	0	0	37.99
ECA	Romania	ROU	0.33	0.29	0.29	0	5.72	1.91	0.96	2.86	19.82
SSA	Rwanda	RWA	57.65	16.68	6.28	21.72	55.24	19.91	9.54	28.15	11.63
SSA	Senegal	SEN	64.94	33.61	21.27	58.26	33.92	10.86	4.97	15.39	14.98
SSA	Seychelles	SYC	3	0.79	0.31	1.03	0.92	0.4	0.25	0.67	0.09
SSA	Sierra Leone	SLE	62.44	44.55	37.17	32	48.46	14.82	6.19	19.8	7.24
SSA	South Africa	ZAF	24.61	7.07	2.59	9.07	18.9	6.2	2.91	8.72	55.29
SA	Sri Lanka	LKA	23.59	5.37	1.8	6.6	0.67	0.09	0.02	0.1	20.97
LAC	St. Lucia	LCA	68.26	31.77	18.65	52.18	6.33	2.94	2.05	3.85	0.18
SSA	Sudan	SDN	43.11	14.66	6.92	20.74	7.67	1.98	0.78	2.59	38.65
LAC	Suriname	SUR	20.34	15.19	13.69	7.54	18.83	14.46	13.24	6.24	0.55
MENA	Syria	SYR	3.81	0.59	0.15	0.7	21.19	4.75	1.58	5.88	18.73
SSA	Tanzania	TZA	69.7	28.32	14.72	42.13	40.69	11.74	4.65	15.31	53.88
EAP	Thailand	THA	19.58	5.02	1.73	6.22	0.03	0.01	0.01	0.02	68.66
SSA	Togo	TGO	39.08	12.43	5.35	16.75	49.15	19.9	10.71	30.45	7.42
EAP	Tonga	TON	6.88	2.01	0.89	2.74	0.95	0.18	0.05	0.21	0.11
LAC	Trinidad Tob.	TTO	0	0	0	0	0.24	0.12	0.12	0.03	1.36
MENA	Tunisia	TUN	16.07	4.17	1.58	5.39	0.39	0.06	0.02	0.07	11.27
ECA	Turkey	TUR	5.57	1.19	0.44	1.46	0.28	0.06	0.03	0.08	78.27
SSA	Uganda	UGA	58.71	26.17	14.88	41.78	39.36	12.31	5.32	16.62	40.14
LAC	Uruguay	URY	0	0	0	0	0.13	0.04	0.02	0.03	3.43
EAP	Vanuatu	VUT	29.16	8.49	3.5	11.29	15.29	3.76	1.41	4.83	0.26
EAP	Vietnam	VNM	76.31	33.94	18.05	50.19	2.35	0.45	0.14	0.55	93.57
MENA	Yemen	YEM	9.69	2.14	0.75	2.71	30.38	8.23	3.19	10.68	26.92
SSA	Zambia	ZMB	47.38	30.02	22.94	73.82	57.5	29.52	18.7	50.72	16.10
SSA	Zimbabwe	ZWE	7.21	1.01	0.2	1.13	16.6	3.63	1.09	4.26	15.78

Note: The table shows each country's headcount poverty (P0), poverty gap (P1), squared poverty gap (P2), and Watts index (W) in the initial and final years of the sample. They are expressed in percentage terms. Population data are taken from PovcalNet database.

APPENDIX B. POVERTY CONVERGENCE CLUBS: DETAILS

TABLE B1. POVERTY CONVERGENCE CLUBS, INCOME AND INEQUALITY

Region	Country	ISO3	Poverty convergence club				Income 1981	Income 2015	Gini (Circa 1981)	Gini (Circa 2015)	Annual income growth (%)	Annual Gini Change (p.p)
			P0	P1	P2	W						
MENA	Algeria	DZA	4	3	3	3	7.97	8.92	40.2	27.62	0.33	-0.55
SSA	Angola	AGO	2	2	2	2	5.7	4.2	51.96	42.72	-0.9	-1.16
SA	Bangladesh	BGD	2	3	3	3	2.8	3.88	25.88	32.13	0.96	0.23
LAC	Belize	BLZ	2	2	2	2	5.94	9.81	60.25	53.26	1.48	-1.17
SSA	Benin	BEN	1	1	1	1	2.31	2.75	38.58	47.76	0.52	0.77
SA	Bhutan	BTN	4	3	3	3	1.56	10.74	40.9	38.81	5.68	-0.23
LAC	Bolivia	BOL	3	3	3	2	8.46	13.93	49.11	46.73	1.47	-0.1
SSA	Botswana	BWA	2	3	3	2	3.08	8.13	54.21	53.33	2.85	-0.03
LAC	Brazil	BRA	4	3	3	3	8.23	19.52	57.95	51.94	2.54	-0.18
ECA	Bulgaria	BGR	4	3	3	3	19.01	19.96	23.43	38.57	0.14	0.58
SSA	Burkina Faso	BFA	1	2	2	2	1.22	2.82	48.07	35.3	2.46	-0.64
SSA	Burundi	BDI	1	1	1	1	1.31	1.7	33.33	38.63	0.77	0.25
SSA	Cabo Verde	CPV	3	3	3	3	2.33	8.36	52.5	42.38	3.76	-0.72
SSA	Cameroon	CMR	2	2	2	2	4.29	5.55	44.45	46.64	0.75	0.12
SSA	Central Afr. Rep.	CAF	1	1	1	1	1.51	1.78	61.33	56.24	0.48	-0.32
SSA	Chad	TCD	2	2	2	2	1.44	3.63	39.83	43.32	2.72	0.44
LAC	Chile	CHL	4	3	3	3	12.16	21.93	56.21	44.37	1.73	-0.42
EAP	China	CHN	4	3	3	3	1.17	11.07	18.46	38.6	6.62	0.59
LAC	Colombia	COL	3	3	3	2	9.26	14.66	53.11	51.1	1.35	-0.07
SSA	Comoros	COM	2	2	2	2	9.06	5.92	55.93	45.34	-1.25	-1.06
SSA	Congo, Dem. Rep.	COD	1	1	1	1	2.15	1.75	42.16	42.1	-0.62	-0.01
SSA	Congo, Rep.	COG	1	1	2	2	2.87	4.16	47.33	48.94	1.1	0.27
LAC	Costa Rica	CRI	4	3	3	3	5.55	23.24	47.5	48.38	4.21	0.03
SSA	Cote d'Ivoire	CIV	1	1	1	1	10.74	3.9	45.53	41.48	-2.98	-0.14
ECA	Czech Republic	CZE	4	3	3	3	16.81	28.61	20.7	25.87	1.56	0.23
MENA	Djibouti	DJI	2	1	1	1	8.65	5.1	40	44.13	-1.56	0.38
LAC	Dominican Rep.	DOM	4	3	3	3	13.51	14.68	47.78	45.18	0.24	-0.09
LAC	Ecuador	ECU	4	3	3	3	7.78	13.96	53.37	45.95	1.72	-0.35
MENA	Egypt, Arab Rep.	EGY	4	3	3	3	3.82	6.1	32	31.82	1.38	-0.01
LAC	El Salvador	SLV	4	3	3	3	8.32	10.29	53.95	40.55	0.63	-0.56
SSA	Eswatini	SWZ	2	2	2	2	0.98	4.21	60.46	51.45	4.28	-0.6
SSA	Ethiopia	ETH	2	3	3	2	2.5	3.13	32.43	34.99	0.66	0.08
EAP	Fiji	FJI	4	3	3	3	6.05	8.09	38.1	36.7	0.86	-0.13
SSA	Gabon	GAB	3	3	3	2	9.1	9.56	42.19	42.19	0.15	0
SSA	Gambia, The	GMB	3	3	3	3	2.07	4.98	48.52	35.92	2.59	-0.74
SSA	Ghana	GHA	3	3	3	2	2.84	6.39	35.35	42.37	2.39	0.28
LAC	Guatemala	GTM	3	3	3	3	4.33	8.98	58.26	48.28	2.15	-0.36
SSA	Guinea	GIN	1	2	2	2	0.83	3.04	46.84	33.73	3.81	-0.62
SSA	Guinea-Bissau	GNB	1	1	1	1	3.47	2.38	43.61	50.66	-1.11	0.42
LAC	Guyana	GUY	3	3	3	3	4.85	10.69	44.55	44.55	2.33	0
LAC	Haiti	HTI	1	1	1	1	5.21	4.42	59.48	60.79	-0.49	0.12
LAC	Honduras	HND	2	3	2	2	4.56	7.78	55.09	49.58	1.57	-0.19
ECA	Hungary	HUN	4	3	3	3	19.69	21.69	20.96	30.41	0.28	0.34
SA	India	IND	3	3	3	2	2.18	4.26	33.33	35.71	1.97	0.09
EAP	Indonesia	IDN	3	3	3	3	1.59	5.81	32.42	42.75	3.81	0.33
MENA	Iran, Islamic Rep.	IRN	4	3	3	3	8.83	16.45	47.42	39.47	1.83	-0.27
MENA	Iraq	IRQ	4	3	3	3	4.43	6.01	28.6	29.54	0.9	0.16
LAC	Jamaica	JAM	4	3	3	3	7.95	11.79	43.16	45.46	1.16	0.14
MENA	Jordan	JOR	4	3	3	3	10.81	10.39	36.06	33.66	-0.12	-0.1
SSA	Kenya	KEN	1	1	1	1	5.68	3.34	57.46	40.78	-1.56	-0.73
EAP	Kiribati	KIR	2	3	2	2	6.47	5.25	36.97	36.97	-0.61	0
EAP	Korea, Republic of	KOR	4	3	3	3	9.32	41.06	31.7	31.56	4.36	-0.02
EAP	Lao People's	LAO	2	3	3	2	2.47	4.13	34.31	36.39	1.51	0.1
MENA	Lebanon	LBN	4	3	3	3	12.92	21.95	31.83	31.83	1.56	0
SSA	Lesotho	LSO	1	1	1	1	3.27	2.9	56.02	51.58	-0.36	-0.28
SSA	Liberia	LBR	1	1	2	2	8.14	2.78	36.48	33.24	-3.16	-0.46
SSA	Madagascar	MDG	1	1	1	1	2.67	1.57	45.26	42.65	-1.56	-0.14
SSA	Malawi	MWI	1	1	1	1	3.66	2.04	65.76	45.48	-1.72	-1.56
EAP	Malaysia	MYS	4	3	3	3	11.96	27.89	48.63	41.04	2.49	-0.25
SSA	Mali	MLI	1	2	2	2	1.1	2.49	50.44	33.04	2.4	-1.16
SSA	Mauritania	MRT	3	3	3	3	3.47	5.74	43.94	32.62	1.48	-0.42
SSA	Mauritius	MUS	4	3	3	3	3.81	14	35.65	38.47	3.83	0.47

LAC	Mexico	MEX	3	3	3	3	11.16	10.06	48.95	48.72	-0.31	-0.01
EAP	Mongolia	MNG	4	3	3	3	4.72	10.23	33.2	32.04	2.28	-0.06
MENA	Morocco	MAR	4	3	3	3	4.9	10.34	39.19	39.55	2.2	0.01
SSA	Mozambique	MOZ	1	1	1	1	1.29	2.77	53.56	54	2.26	0.02
EAP	Myanmar	MMR	3	3	3	3	0.94	5.75	38.07	38.07	5.32	0
SSA	Namibia	NAM	3	3	3	3	8.39	11.38	63.32	59.07	0.9	-0.35
SA	Nepal	NPL	3	3	3	3	1.57	4.8	30.06	32.84	3.28	0.11
LAC	Nicaragua	NIC	4	3	3	3	7.75	11.42	57.36	46.16	1.14	-0.53
SSA	Niger	NER	1	2	2	2	2.36	2.63	36.1	34.28	0.32	-0.08
SSA	Nigeria	NGA	1	1	2	2	3.01	2.85	38.68	42.97	-0.16	0.18
SA	Pakistan	PAK	3	3	3	3	1.75	4.73	33.32	33.45	2.93	0.01
LAC	Panama	PAN	4	3	3	3	12.16	23.83	58.91	50.81	1.98	-0.31
EAP	Papua New Guinea	PNG	2	2	2	2	2.47	3.96	45.77	41.85	1.4	-0.3
LAC	Paraguay	PRY	4	3	3	3	13.18	17.05	40.84	47.61	0.76	0.27
LAC	Peru	PER	3	3	3	3	14.45	13.12	45.64	43.36	-0.28	-0.08
EAP	Philippines	PHL	3	3	3	3	4.29	6.08	41.04	40.11	1.03	-0.03
ECA	Poland	POL	4	3	3	3	12.57	17.32	25.17	31.75	0.94	0.22
ECA	Romania	ROU	3	3	3	2	13.13	10.48	23.31	35.91	-0.66	0.49
SSA	Rwanda	RWA	1	1	1	1	2.12	2.68	48.55	45.11	0.69	-0.26
SSA	Senegal	SEN	2	2	2	2	2.33	3.46	54.14	40.29	1.17	-0.69
SSA	Seychelles	SYC	4	3	3	3	11.07	24.6	42.78	46.82	2.35	0.29
SSA	Sierra Leone	SLE	1	2	2	2	2.29	2.5	40.17	34.03	0.25	-0.77
SSA	South Africa	ZAF	2	3	2	2	8.64	11.26	59.33	63.03	0.78	0.18
SA	Sri Lanka	LKA	4	3	3	3	3.47	9.18	32.47	39.16	2.87	0.25
LAC	St. Lucia	LCA	4	3	3	3	1.86	16.3	42.58	42.58	6.39	0
SSA	Sudan	SDN	3	3	3	3	2.65	5.95	35.4	34.24	2.38	-0.23
LAC	Suriname	SUR	2	1	1	2	9.33	10.98	57.61	57.61	0.48	0
MENA	Syrian Arab Rep.	SYR	2	3	2	2	6.19	3.84	35.78	35.78	-1.4	0
SSA	Tanzania	TZA	1	2	2	2	1.79	2.94	35.29	37.78	1.46	0.13
EAP	Thailand	THA	4	3	3	3	5.54	15.65	45.22	35.99	3.06	-0.27
SSA	Togo	TGO	1	1	1	1	3.36	2.75	42.21	43.06	-0.59	0.09
EAP	Tonga	TON	4	3	3	3	6.76	10.22	37.69	37.59	1.22	-0.01
LAC	Trinidad Tobago	TTO	4	3	3	3	21.06	26.02	42.6	40.27	0.62	-0.58
MENA	Tunisia	TUN	4	3	3	3	5.59	11.05	43.43	32.82	2	-0.35
ECA	Turkey	TUR	4	3	3	3	7.53	18.04	43.48	42.85	2.57	-0.02
SSA	Uganda	UGA	2	2	2	2	2.29	3.29	44.36	41.01	1.07	-0.15
LAC	Uruguay	URY	4	3	3	3	19.35	27	40.2	40.12	0.98	0
EAP	Vanuatu	VUT	2	3	3	2	3.52	4.72	37.63	37.63	0.87	0
EAP	Vietnam	VNM	4	3	3	3	1.59	9.04	35.65	34.76	5.11	-0.04
MENA	Yemen, Rep.	YEM	1	1	2	2	5.31	3.34	35	36.71	-1.36	0.11
SSA	Zambia	ZMB	1	1	1	1	4.03	3.03	60.51	57.14	-0.84	-0.14
SSA	Zimbabwe	ZWE	1	1	2	1	7.32	5.55	43.15	43.15	-0.81	0

Note: The table shows each country's poverty club membership for headcount poverty (P0), poverty gap (P1), squared poverty gap (P2), and Watts index (W), along with its per capita income (in 2011 PPP-adjusted USD per day and Gini index (in percent) in the initial and final years of the sample, plus their average rate of change over the sample period.