

POVERTY CONVERGENCE CLUBS

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Abstract

Global eradication of extreme poverty requires absolute convergence of poverty rates worldwide towards zero. Empirical analysis of poverty data for a hundred emerging and developing countries over four decades reveals that such goal is likely to remain elusive. Rather than absolute convergence, we find club convergence: countries' long-run poverty rates cluster into several distinct clubs, whose number depends on the specific poverty dimension considered. Only the lowest-poverty club exhibits poverty rates approaching zero by the end of the sample. In contrast, the highest-poverty club, which accounts for nearly half the world's poor, evokes a poverty trap: its average poverty barely budged over the entire period examined. Overall, income -- its initial level and, especially, its growth rate -- matters more than inequality for shaping countries' club membership, particularly for the highest-poverty club. Nevertheless, inequality plays a substantive role for membership in the intermediate-poverty clubs, which achieved the greatest poverty reduction.

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

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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: in 2019, people living below the poverty line of US\$2.15 (in 2017 PPP dollars) still represent 8.4% of the world population (648 million people). Moreover, poverty rates display considerable variation between and within world regions (World Bank, 2022).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 a large sample of 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 (Johnson & Papageorgiou, 2020).

This paper is, as far as we are aware, the first to perform formal tests of the hypothesis of club convergence in absolute poverty. Conceptually, a poverty convergence club is a set of countries whose poverty rates may differ over an extended period, but converge to one another in the long-run (Galor, 1996). 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 & Johnson, 1995; Islam, 2003). Instead, we use the panel clustering testing approach of Phillips & Sul (2007; 2009). Building on a nonlinear factor model with time-varying loadings, it can be used to test a variety of hypotheses on the series dynamics, including divergence, club

¹ Between 1990 and 2019, the average headcount poverty rate fell from 65.8% to 1.1% in East Asia and the Pacific, from 16.7% to 4.3% in Latin America and the Caribbean, and from 49.7% to 8.5% in South Asia. In sub-Saharan Africa, the poverty rate fell by almost 19 percentage points between 1990 and 2019, but 35.1% of the region's population (some 421 million people) still live below the \$2.15 poverty line. There are also large differences between countries within each region. In South Asia, for example, the headcount poverty rate fell from around 41% to 7% in Bangladesh and from around 13% to almost zero in Sri Lanka between 1990 and 2019. The contrast is even starker in sub-Saharan Africa: In Zambia, the headcount poverty rate rose from about 56% to 61%, while in Namibia it fell from about 54% to 17% over the same period.

convergence, and both absolute and conditional convergence, without the need of specific assumptions regarding the order of integration of the series.²

Using data for a sample of 100 emerging and developing countries over 1981-2019, we unambiguously reject the hypotheses of absolute and conditional convergence. Instead, we find strong evidence of club convergence: four clubs for the scale of poverty (as captured by the headcount), and two or 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 four decades. Out of the 614 million poor in our sample countries in the final year of analysis, 259 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 (Azariadis & Stachurski, 2005; Bowles et al., 2006).

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 since the mid-1990s, 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. 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. Likewise, 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.

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 in Section 2), we assume that these two variables summarize the fundamental factors

² An alternative method for analyzing club convergence is the use of mixture models (Owen et al., 2009; Pittau et al., 2010; Battisti & Parmeter, 2013), based on the 'distribution dynamics' approach pioneered by Quah (1997). It yields estimates of the probability that each country's observations are drawn from a particular distribution in the mixture, offering a natural metric for assigning countries to specific clubs. The method requires the identification of multiple mixture components, an examination of the parameters associated with those components, and an assessment of the mobility of countries over time, as outlined by Pittau et al. (2016).

driving poverty dynamics (and hence club formation). Since our dependent variable, club membership, is an ordinal discrete variable, we estimate an ordered response model (McKelvey & Zavoina, 1975; Greene & 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.³

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 also 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 correctly predict countries' poverty club membership.

For all four poverty measures considered and the entire sample, we find that the biggest contributors to the formation of poverty clubs are initial income and its change over time, while inequality plays a secondary role in shaping poverty club membership. However, closer examination of our results yields additional insights, which apply to all the poverty measures considered. First, 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 initial income and its growth rate, while inequality does not play a major role. Lastly, initial conditions have contributed relatively little to countries' membership in intermediate-poverty clubs. The inequality dimension matters more for membership in these clubs than it does for membership in the highest-poverty clubs.

³ 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 & Papageorgiou, 2020). The key difference between club convergence and other forms of convergence, such as absolute and conditional convergence, is that initial conditions also play a role in the dynamic process. Thus, differences in initial conditions can become permanent: countries experiencing similar shocks to economic fundamentals (captured by changes in income and inequality) along the transition path may converge to different long run poverty rates if their initial conditions (captured by initial income and inequality levels) are sufficiently different.

The rest of the paper is structured as follows. In Section 2, we explain our contribution to the literature. In Section 3, we provide an overview of the poverty data used and conduct a classical convergence analysis. In Section 4, we describe the implementation of our club convergence methodology and the main empirical results for the alternative poverty measures considered. In Section 5, 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 6 presents the main conclusions.

2. CONTRIBUTION TO THE LITERATURE

Our paper is embedded in an extensive literature on convergence (recently surveyed by Johnson & Papageorgiou, 2020; Kremer et al., 2021) and on the multidirectional links among poverty, growth and inequality (recently surveyed by Cerra et al., 2021; Marrero & 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-Martin (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 & 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.⁴ Overall, poverty convergence remains an open question. We contribute to this literature by bringing the club convergence perspective and offering formal tests of club convergence in absolute poverty.⁵

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.

⁵ The existence of poverty convergence clubs is explained by non-linearities in the relationship between poverty and its main driving forces, namely income and inequality. Van der Weide & Milanovic (2018) and Marrero et al. (2021) show that there is also a non-linear relation between the latter two variables: inequality has different effects on the income prospects of different parts of the distribution (i.e., negative for the poor and positive or insignificant for the rich).

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 & Riedl, 2012; Phillips & Sul, 2009). This paper applies this approach to poverty. 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 & 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 & Verschoor (2007) or Fosu (2017). More recently, Bergstrom (2020) or Lakner et al. (2022) 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 examining how those contributions may vary across clubs.

3. ABSOLUTE POVERTY DYNAMICS AROUND THE WORLD

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

$$P(z) = \int_0^{P_0} \Omega[y(q); z] dq, \tag{1}$$

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 to save notation) and $P_0 = F(z)$, 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 (letting $\theta = 0$) P_0 , the poverty gap ($\theta = 1$), henceforth denoted P_1 , and the squared poverty gap ($\theta = 2$), denoted P_2 . 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. P_0 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, P_1 provides a measure of poverty *intensity*, as it shows the (average) shortfall of the income of the poor relative to the poverty line. P_2 and W capture the *severity* of poverty. P_2 weighs 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, W places a bigger weight than P_2 on very low incomes, and a lower weight on the incomes of less-poor individuals.⁶

Time-series data on these poverty measures are taken from PovcalNet, using a poverty line of US\$2.15 per individual per day at 2017 PPP, which replaces the earlier threshold of US\$1.90 per individual per day at 2011 PPP (Ferreira et al., 2016).⁷ PovcalNet's poverty estimates are constructed from household surveys. 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.

From the initial set of 166 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, since their absolute poverty levels are zero or very close to zero for all measures and years in the sample. Lastly, we drop countries

⁶ Under lognormality, W 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 W divided by the rate of growth of the income of the poor.

⁷ Poverty estimates are homogenized using PPP exchange rates for household consumption from the 2017 International Comparison Program.

with less than two surveys during the period and those with incomplete time series.⁸ Thus, our final sample consists of 100 emerging and developing countries over the period 1981-2019⁹ (see Appendix A for details).

Table 1 reports descriptive statistics for the four poverty measures in 1981 and 2019, 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 35%, 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 2019 the averages of all four measures exhibit a substantial reduction. Average P0 falls from 35% in 1993 to 17% in 2019, which amounts to a reduction of 0.7 percentage points (p.p.) per year. Over the same period, average P1, P2 and W similarly decline by 0.36, 0.23 and 0.61 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 2019 than in 1981 (see Table 1). The time path of their 25th-75th 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.

As a preliminary exploration of poverty convergence, Figure 2 shows the relationship between the annual change in poverty (in p.p.) between 1981 and 2019 and its initial level (in 1981) for the four poverty measures considered (i.e., absolute β -convergence graphs). 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. Globally, absolute poverty is not diverging. However, cross-sectional regressions of poverty changes on initial poverty do not discriminate between absolute convergence and other types of convergence (Durlauf & Johnson, 1995; Quah, 1993; 1996).

⁸ For those reasons, we drop Guyana, Lebanon, Marshall Islands, Micronesia, Nauru, Samoa, South Sudan, Suriname, Timor Leste, Tuvalu and Venezuela, as well as the former Yugoslavia and Soviet Union countries, as in Ravallion (2012), since these latter countries display atypical behaviour due to their transition from socialist to market economies.

⁹ PovcalNet also provides information for 2020 and 2021, but at present only for a few countries.

A more informative graphical tool is the distribution of poverty indices over time, which is useful for visualizing long-term trends in poverty across countries and detecting potential accumulation points suggestive of club convergence (Quah, 1997; Pittau et al., 2010). For the four poverty measures considered, Figure 3 shows these distributions for the beginning (1981), the middle (2000) and the end of the sample period (2019).

In all cases, there is a steady decline in the mean of the distribution, so that in 2019 it is about half of its 1981 value. Moreover, all distributions show a thinning in the middle and are at least bimodal or, to use the term coined by Quah (1997), twin-peaked, with one mode corresponding to low poverty levels and the other to high poverty levels. For example, for the headcount, one peak is located between 0 and 0.15 and another between 0.6 and 0.7, depending on the year.¹⁰

As the figure shows, the global mode is the lower-poverty one. Moreover, its density has increased over the years. In 2019, there are many more countries around the low-poverty mode than in 1981 or 2000. In fact, the distributions in 1981 and in 2000 resemble each other more closely than they resemble the 2019 distribution. While poverty shows a downward trend over the entire sample period, the gap between the high- and low-poverty modes has widened. For example, for the headcount poverty rate, it was about 50 p.p. in 1981 and 2000, while it is about 65 p.p. in 2019.

Multimodal cross-country distributions may reflect the existence of convergence clubs, with each mode corresponding to a convergence club. However, multimodality is neither necessary nor sufficient for convergence clubs to exist (Pittau et al., 2010). 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.

4. POVERTY CONVERGENCE CLUBS: EMPIRICAL RESULTS

In this Section we describe the implementation of the Phillip & Sul (2007) club convergence method and the main empirical results for the alternative poverty measures considered. To save space, technical details are relegated to several appendices.

¹⁰ In some cases, another mode is also observed for intermediate values of the poverty rate. This is the case of the headcount poverty rate in 2019, which exhibits another mode at around 0.20.

4.1. Implementation

Implementation of the Philips and Sul (henceforth P-S) approach (described in detail in Appendix B) requires a balanced panel dataset, and we use interpolated annual data from PovcalNet on the different measures of poverty over the 1981-2019 period. The P-S approach focuses on the long-term component of the variable of interest. Prior to its empirical implementation, it is necessary to purge the data of cyclical components and short-term noise through a suitable form of smoothing. For this purpose, P-S specifically suggest using the Hodrick & Prescott (1997) filter (HP), because it is well-suited to short time series, it does not require prior specification of the nature of the time series trends, and the only input it needs is the value of the smoothing parameter. In their application to annual data, P-S use the HP filter with a smoothing parameter of 400, which probably leads to excess smoothing. Indeed, the seminal paper of Hodrick & Prescott (1997) uses a smoothing parameter of 100.

Ravn & Uhlig (2002) propose a general rule for selecting the smoothing parameter under different data frequencies. In our baseline specification, we follow Ravn & Uhlig's rule and set the smoothing parameter at 6.25.¹¹ This amounts to a cautious choice that applies minimal filtering to the original series. Nevertheless, because the choice of smoothing parameter may affect the empirical results obtained with the P-S approach (Tomal, 2023), we perform additional experiments with smoothing parameter values of 100 and 400. They show that the qualitative results regarding the number of clubs and club membership remain largely unchanged (see Appendix C).¹²

4.2. Results

We first test the null hypothesis of absolute convergence for the four poverty measures considered by estimating Philips and Sul's so-called *log-t* regression (Equation (B4) in Appendix B). Detailed results for the parameters and statistics of this regression (omitted here to save

¹¹ According to the Ravn and Uhlig rule, the value of the smoothing parameter is obtained multiplying the value of the smoothing parameter of the HP filter conventionally used to detrend quarterly time series ($\lambda = 1600$) by the inverse of the fourth power of the frequency of observation as compared to quarterly data (α): $\frac{1}{\alpha^4}\lambda$. In our case, for annual data, $\alpha = 4$, thus the smoothing parameter is $\frac{1}{4^4}1600 = 6.25$.

¹² A few countries featuring medium or high poverty rates at the end of the sample period do change their club membership when the value of the smoothing parameter changes. This is not a weakness of the method, but rather an expected occurrence, as these countries are likely to be close to more than one steady state, unlike countries that are unambiguously converging to a lower or higher poverty level.

space) are shown in Table B1 in Appendix B. In all cases, we unambiguously reject both absolute and conditional convergence for the full sample -- in spite of the appearance of absolute convergence that a naïve look at Figure 2 might suggest.

Second, we use the clustering algorithm described in P-S to differentiate between global divergence and club convergence. The procedure reveals club convergence: four clubs for the headcount poverty rate, three for poverty gap and Watts, and two for the squared poverty gap. The detailed list of countries belonging to each club is shown in Table 2, with clubs arranged in descending order of long-run poverty -- i.e., Club 1 is the club with the highest long-run levels of poverty.

These results are consistent with the poverty distributions shown in Figure 3. For P0, the two accumulation points seen in the distribution correspond mostly to countries in Club 4, for the low-poverty mode, and to Clubs 1, 2, and 3 for the high-poverty mode. The flatness of the distribution around the high-poverty mode seems to conceal the existence of multiple clubs, which is revealed by the P-S approach. A similar situation occurs for P1 and W, while for P2 the P-S approach confirms the visual bi-modal distribution shown in Figure 3.

For each poverty measure, Table 3 summarizes the main characteristics for the full sample and 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. For P0, P1, P2 and W, the average levels of poverty in 2019 are 46.9%, 20%, 9.8% and 28.7% in the highest-poverty clubs, and 1.8%, 0.9%, 1.3% and 1% in the lowest-poverty clubs, respectively.

Figure 4 shows the time path of the cross-sectional mean (with its 90% confidence interval) 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, Club 2 for P2 and Club 3 for P1 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 2019.

Intermediate clubs (Clubs 2 and 3 for P0 and Club 2 for P1 and W) show the largest extent of poverty reduction over the sample period. For headcount poverty, the comparison between Clubs 2 and 3 is interesting. Their poverty levels approach each other until becoming virtually identical by the mid-1990s. 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.¹³

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 3 shows that, depending on the poverty measure under consideration, they roughly represent between 50% and 80% of the country sample. In turn, countries in the intermediate-poverty clubs are making progress towards reduced, 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 40 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 2019.¹⁴ Figure 5 shows the distribution that results for each of the poverty measures considered. The total number of poor in our sample in 2019 equals 614 million. Out of that total, 259 million (42%) live in countries "trapped" in Club 1 of headcount poverty. At the other end, only 57 million live in countries approaching complete poverty eradication (i.e., belonging to Club 4 of headcount poverty). Moreover, Figure 5 also shows that, of those 259 million trapped in a high-poverty equilibrium, about 71% (183 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 76% (196 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).¹⁵ Overall, the conclusion is that global poverty eradication is likely to remain elusive on current trends.

¹³ For instance, within Club 2 we find countries such as Chad and Ghana, which reduced their headcount poverty rates by around 36 p.p. between 1996 and 2019, 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 39 years, managed to bring them close to zero. This is the case, for example, of Senegal and India. In addition, for the poverty gap and the Watts index, 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 and W around 25% and 35%, respectively. This is because several countries from Club 2 in both measures (i.e., Burkina Faso and Eswatini) started in 1981 with very high levels of P1 and W and managed to reduce them sharply by 2019. In contrast, other countries from Club 1 (i.e., Madagascar and Malawi) started with smaller levels of P1 and W but failed to reduce them by the end of the sample period.

¹⁴ We calculate the number of poor in each country multiplying its 2019 headcount poverty rate by its total population in the same year. Both magnitudes are shown in Table A1 in Appendix A.

¹⁵ These observations are based on the fact that, as Table 2 shows, all countries belonging to Club 1 under P1, P2 and Watts also belong to Club 1 of headcount poverty. The only exceptions are Benin, Cote d'Ivoire and Sao Tome and Principe. However, their combined total number of poor in 2019 is just 5 million, which is immaterial for the calculations in the text.

To conclude this section, we should emphasize that the poverty clubs we identify differ from conventional groupings based on countries' geographic location or their observed levels of poverty or per capita income.

Geographic location does matter for club membership, especially for the highest-poverty club, but it is far from being the only factor at play (see Table A2 in Appendix A). For instance, while countries in Sub-Saharan Africa account for most of the membership in Club 1 (i.e., 78%, 76%, 80% and 79% of the member countries for P0, P1, P2 and W, respectively), around 25% of the region's countries belong to clubs with lower poverty levels. Moreover, membership in all the other clubs is geographically quite diverse: intermediate clubs comprise countries from Sub-Saharan Africa, Latin America and the Caribbean, East Asia and Pacific and South Asia, while lower-poverty clubs include countries from all regions.

Similarly, we show in Figure 6 that the poverty clubs we find 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.¹⁶ Nor do the country groups defined by the poverty clubs match the groups derived from conventional classifications based on countries' per capita income, such as the World Bank income classification as of 2019 (see Figure 6). 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.

These comparisons serve 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 or income at any particular moment of the sample. Thus, the club-based clustering provides independent information relative to that provided by standard income-based or current poverty-based clustering.

5. 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), poverty can be

¹⁶ If that were the case, every country in Club 1, for example, would exhibit higher poverty in 2019 than every country in Club 2, and the same would apply to Club 2 vs Club 3, and so on. Figure 6 clearly shows that this is not the case: there is considerable overlap between the ranges of 2019 poverty rates of the various clubs, even between those of the highest- and lowest-poverty clubs.

seen to be a function of mean per capita income and a suitable 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.

Generally, the empirical literature (Bourguignon, 2003; Kraay, 2006; Ferreira, 2012; Chen & Ravallion, 2010 or Dollar & Kraay, 2002, among many others) that has sought to quantify the respective contributions of income and inequality to poverty employs a linear (or log-linear) specification, such as:

$$P_{it} = \alpha_i + \gamma \log \bar{y}_{it} + \varphi G_{it} + v_{it}, \quad (2)$$

where \bar{y}_{it} is mean per capita income and inequality (G_{it}) is typically measured by the Gini index. Equation (2) can be derived from the analytical framework summarized in Appendix D.

Based on 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.

5.1. An ordered response model of poverty club membership

To get a quantitative assessment of the respective roles of income and inequality for poverty club formation, we estimate an empirical model of poverty club membership. Membership is an ordinal discrete variable which takes values from 1 up to the maximum number of clubs, which varies across poverty measures. Thus, we estimate an ordered logit model relating club membership (as obtained from the P-S's clustering approach) to initial conditions and changes in mean income and the Gini index. In practical terms, (see Appendix D for more details), we estimate:

$$P_i^* = \beta_1 \log y_{it_0} + \varphi_1 G_{it_0} + \beta_2 \Delta \log y_i + \varphi_2 \Delta G_i + \varepsilon_i, \quad (3)$$

where P_i^* is an unobserved latent variable, which represents the steady-state level of poverty; y_{t_0} and G_{t_0} respectively denote the initial values of mean income and the Gini index, and $\Delta \log y_i$ and ΔG_i are their changes over the sample period.¹⁷

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 affecting the transition.

Second, how big is the role of inequality in determining poverty club membership? The empirical literature referenced in Section 2 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 poverty measures.

To assess both of these issues, we compare the results from estimating the full model (3) with those from two suitably restricted models, the first one including only initial conditions and the second only income variables:

$$P_i^* = \beta_{11} \log y_{it_0} + \varphi_{11} G_{it_0} + v_i, \quad (4)$$

$$P_i^* = \beta_{12} \log y_{it_0} + \beta_{22} \Delta \log y_i + w_i. \quad (5)$$

The larger the difference between the explanatory powers of models (3) and (4), 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 (3) and (5), the more relevant is the role of the initial Gini index and its subsequent changes, given income.

¹⁷ We should caution that estimation of the ordered logit model implicitly assumes that the club classification obtained from the Phillips & Sul clustering procedure is exact, as do other papers using this strategy (Bartkowska & Riedl, 2012; Cavallaro & Villani, 2022; Belloc & Molina, 2023, among others). To the extent that it is not, our results will tend to overstate the precision of the logit estimates. There is no simple way to correct for this, as it would essentially require modelling the sampling error of the P-S procedure. Still, to the extent that our main result – i.e., the dominant role of income vis-à-vis inequality in shaping long-run poverty trends in the sample – is fully consistent with the findings of earlier literature employing very different techniques, we are confident that our estimates of the respective contributions of income and inequality should not be too far off their true values.

5.2. 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 4 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) (see Table A2 in Appendix A for the full details on income and inequality by country). PovcalNet provides interpolated information on mean income (thus, we have data for 1981 and 2019 in all cases), but it does not provide interpolated information on the Gini index and other inequality measures. When 1981 and/or 2019 data on the Gini index are not available, we use the value from the survey closest to the missing year.

A preliminary inspection of Table 4 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 almost zero or negative for the highest-poverty club (Club 1), while it reaches around 2% per year for the lowest-poverty club (Club 4 for P0, Club 2 for P2 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 as 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 measures, although the reduction appears more marked for the intermediate clubs. 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 4 for the cases of P1 and W, and Clubs 2 and 3 of P0.

5.3. Estimation results of the ordered logit model

Table 5 reports the parameter estimates of equations (3)-(5) for headcount poverty and for the other poverty measures, respectively. In general, all coefficients are significant and carry 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 5).¹⁸ 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 31% when the growth rate of income increases 0.1 p.p. per year ($1 - 1/e^{3.72 \cdot 0.1} = 0.31$). Over the 39-year sample period (i.e., between 1981 and 2019), this is equivalent to an income growth of 3.9%, which should be compared with the average growth rate of the entire sample ($1.38 \cdot 39 = 54\%$, see Table 4). This simple quantitative exercise shows the importance of income growth for escaping extreme poverty (i.e., moving from a higher-poverty club to a lower-poverty club).

As for the Gini index, the odds of belonging to the highest-poverty club, relative to the rest, decrease by 27% when the initial Gini index decreases 1 p.p. ($1 - e^{-0.31} = 0.27$). Likewise, the odds decrease 31% following an annual reduction of 0.1 p.p. in the Gini index ($1 - e^{-\frac{3.77}{10}} = 0.31$). Such annual reduction would entail a drop in the Gini index of 3.9 p.p. over the 39-year sample period, which is a significant but not infeasible amount.

Table 5 also reports McFadden's pseudo-R², which summarizes the overall explanatory power of each model. For the full model (3), the values are quite high, regardless of the poverty measure considered (0.66 for P0, 0.60 for P1 and W, and above 0.50 for P2).¹⁹ 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 in placing each country in its corresponding club. The first restricted model (4), which includes initial conditions only, yields

¹⁸ 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.

¹⁹ 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 & 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).

a pseudo-R2 below 0.11 for all poverty measures, far below the values obtained with the full model. The second restricted model (5), which includes income variables only, yields a pseudo-R2 of about 0.50 for all poverty measures, closer to, but still below, those from the full model, with the gap being particularly large for P0. 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 P0 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. The dominance statistics of the individual regressors add up to the pseudo-R2 value (Budescu 1993; Grömping 2007).²⁰

Table 6 reports the dominance statistics of the full model (3) for each of the four poverty measures. The table shows that initial income and, especially, annual income growth, are consistently the most dominant factors. For P0, initial income almost plays the leading role, while for the other poverty measures income growth is clearly the most dominant factor.

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: contrary to what occurs with income, initial inequality contributes more to the overall fit, while the change in inequality plays a more modest role.

If we do not use interpolated income data, so that we exclusively have income and inequality data extracted from surveys closest to the beginning (1981) and end of the period (2019), the results do not change substantially. The role of income growth diminishes, while the role of inequality remains unchanged.

5.4. Predicting club membership

The preceding discussion focused on the ability of the empirical models (3)-(5) to explain overall club formation, as well as on the contributions of income and inequality, their initial conditions and subsequent changes, to that explanatory power. However, this may still yield an incomplete picture, in that the models' explanatory ability, and the roles of the different variables, are likely to vary, perhaps widely, across clubs.

²⁰ 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 (Luchman, 2013).

To address this question, we use a prediction exercise. Specifically, we analyze the ability of the empirical specifications (3)-(5) to correctly predict countries' membership in the different clubs, and assess the respective roles of income and inequality, as well as their initial conditions and performance over time, in shaping the accuracy of such predictions.

Hence, we use the estimates of the ordered logit models (3)-(5) 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 P-S clustering procedure (Table 3). For each poverty measure, we compute the number and percentage of countries whose club membership is correctly/incorrectly predicted – thus building so-called confusion matrices (Ting, 2011). In this way, we can also identify the specific countries for which the restricted and the full-model predictions differ.

The main objective of this exercise is to provide insights on how the roles of the different variables shaping club membership vary across clubs. Thus, we break down by club the prediction accuracy analysis. For each estimated model, Table 7 shows the number and percentage of countries whose club membership is correctly/incorrectly predicted (i.e., the confusion matrices by club). 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.

In addition, in Table E1 in Appendix E we show the predictive accuracy of each model over the full country sample, given by the sum of the main diagonals of Table 7. When performing this exercise, we obtain the same conclusions as in the preceding subsection: income plays a bigger role than inequality, and income growth matters more than initial income, while initial inequality plays a bigger role than its changes over time.

When examining Table 7, we can extract three main conclusions. First, membership in the lowest-poverty club is well predicted by all models. In all cases, the percentage of successful predictions exceeds 90% (i.e., the lowest percentage is 92% for the full and initial conditions-only models for P0). Interestingly, the model featuring initial conditions only does nearly as well (even better, in the case of P2) 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 78 percent of the cases) and less so for the rest of poverty measures (around 60 percent successful predictions). This suggests that 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.²¹

In contrast, initial conditions play a secondary role when explaining countries' membership in the highest-poverty club. For P0, the initial conditions-only model correctly predicts 48 percent of the Club 1 membership, while for the other poverty measures, the success rate at predicting membership in this club is 21 percent or less. 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 and decreases in their income levels between 1981 and 2019.²²

Third, the various models generally have a harder time at predicting membership in intermediate-poverty clubs in P0, P1 and W. The initial conditions-only model does especially poorly in this regard, as 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.²³

The income-only model does better at predicting intermediate-club membership – but the success rate of its predictions is in all cases below that of the full model. This underperformance is especially visible for P0, where the success rate of the income-only model at predicting

²¹ Two relevant examples for P0 are those of Burkina Faso and Eswatini, 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.

²² Examples are Republic of Congo, Syria and Zimbabwe.

²³ 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 Botswana, Gambia, Guatemala, Honduras and Senegal. 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 Club 2 is 16 p.p. lower than that of the full model. From this we can conclude that the inequality dimension plays a more substantive role in determining membership in intermediate-poverty clubs.²⁴ This stands in contrast with membership in the highest-poverty clubs, for which inequality has played a limited role over the time sample considered, as we saw above.²⁵

6. CONCLUSIONS

In this paper we have analysed the dynamics of different dimensions of poverty using a large cross-country panel dataset comprising a hundred emerging and developing countries over almost four decades. Importantly, 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.

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

²⁴ The predictive power of the estimated models declines when we use income and inequality data derived exclusively from surveys. This is particularly reflected in the reduced ability of income and inequality to correctly predict countries' membership in intermediate clubs.

²⁵ 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., Solomon Islands and Sudan). In contrast, the full model, inclusive of inequality, predicts club membership correctly in these cases.

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 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 also yields insights on 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. In contrast, for countries belonging to intermediate-poverty clubs, income still plays the dominant role, but inequality also matters for their club membership.

In summary, 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. Yet this does not necessarily imply that the secondary role of inequality found in the sample for the poorest countries must persist also in the future. Even very poor countries might be able to deploy redistributive policies -- such as targeted expenditures or tax reforms – more actively in the future than done over the sample period, thus enhancing the contribution of inequality to the trends in their poverty rates. Likewise, 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.

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TABLES

TABLE 1. ABSOLUTE POVERTY: DESCRIPTIVE STATISTICS

	Headcount (P0)			Poverty gap (P1)			Squared poverty gap (P2)			Watts (W)		
	1981	2019	Annual p.p. change	1981	2019	Annual p.p. change	1981	2019	Annual p.p. change	1981	2019	Annual p.p. change
mean	35.89	16.70	-0.52	16.09	5.98	-0.28	9.50	3.00	-0.18	26.60	8.74	-0.49
sd	29.09	20.60	-0.23	16.29	8.99	-0.20	11.19	5.13	-0.16	31.20	14.20	-0.46
p25	7.67	1.03	-0.20	2.23	0.26	-0.05	0.92	0.09	-0.02	2.97	0.30	-0.07
p50	29.05	6.80	-0.55	9.80	1.90	-0.22	5.34	0.63	-0.14	13.14	2.40	-0.30
p75	61.66	24.87	-1.01	26.66	8.04	-0.50	15.23	3.32	-0.31	42.98	10.92	-0.83

Notes: 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. POVERTY CLUB MEMBERSHIP

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

Notes: 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 highest-poverty club under all poverty measures. Countries underlined belong to the lowest-poverty club under all poverty measures.

TABLE 3. ABSOLUTE POVERTY: CONVERGENCE CLUBS

Measure	Club	Number of countries	Absolute poverty rate (average)		
			1981	2019	Annual p.p. change
Headcount (P0)	Club1	23	51.06	46.9	-0.11
	Club2	12	37.13	24.79	-0.32
	Club3	13	52.06	12.06	-1.05
	Club4	50	23.92	1.77	-0.58
	<i>Divergent units</i>	2			
	Full sample	100	35.89	16.70	-0.52
Poverty gap (P1)	Club1	17	20.24	20.05	0.00
	Club2	23	20.47	8.83	-0.31
	Club3	60	13.24	0.89	-0.32
	Full sample	100	16.09	5.98	-0.28
Squared poverty gap (P2)	Club1	20	10.81	9.75	-0.03
	Club2	80	9.17	1.32	-0.21
	Full sample	100	9.50	3.00	-0.18
Watts (W)	Club1	19	32.73	28.69	-0.11
	Club2	23	36.55	11.84	-0.65
	Club3	58	20.65	0.98	-0.52
	Full sample	100	26.60	8.74	-0.49

Note: For each poverty club under each poverty measure, the third column shows the number of member countries and 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.

TABLE 4. INCOME AND INEQUALITY: DESCRIPTIVE STATISTICS BY CLUB

		Income 1981		Income 2019		Gini (circa 1981)		Gini (circa 2019)		Annual income growth (%)		Annual Gini change (p.p)	
		mean	sd	mean	sd	mean	sd	Mean	sd	mean	sd	mean	sd
Headcount (P0)	Club 1	3.96	2.50	3.79	1.64	48.30	10.00	45.07	6.43	0.17	1.80	-0.17	0.50
	Club 2	5.36	3.65	5.27	2.25	43.15	9.32	41.94	8.36	0.30	1.56	-0.22	0.63
	Club 3	4.07	2.85	6.75	2.47	47.74	10.91	40.09	9.07	1.75	1.43	-0.36	0.29
	Club 4	8.29	5.42	16.38	8.62	41.34	9.01	38.43	6.65	2.12	1.72	-0.22	0.59
Poverty gap (P1)	Club 1	4.58	2.68	3.66	1.72	46.63	10.08	44.10	7.54	-0.42	1.41	-0.10	0.51
	Club 2	4.59	3.20	5.15	2.11	46.26	9.58	42.82	7.08	0.71	1.64	-0.28	0.51
	Club 3	7.44	5.37	14.76	8.73	42.42	9.66	38.75	7.19	2.14	1.61	-0.24	0.55
Squared poverty gap (P2)	Club 1	4.97	2.69	3.95	1.77	46.91	10.35	43.83	7.00	-0.46	1.31	-0.15	0.55
	Club 2	6.63	5.10	12.34	8.71	43.30	9.60	39.79	7.46	1.83	1.70	-0.25	0.53
Watts (W)	Club 1	4.93	2.76	3.86	1.77	47.69	10.02	43.99	7.16	-0.48	1.34	-0.18	0.54
	Club 2	4.18	3.03	5.26	2.27	45.63	9.19	42.92	7.58	0.96	1.59	-0.22	0.47
	Club 3	7.59	5.40	15.03	8.74	42.18	9.69	38.56	7.03	2.15	1.63	-0.24	0.56
	Full sample	6.30	4.76	10.66	8.51	44.02	9.81	40.60	7.51	1.38	1.87	-0.23	0.53

Note: The table shows, for each poverty club under each poverty measure, the average levels of income (expressed in 2017 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 5. ORDERED LOGIT MODEL ESTIMATION RESULTS. HEADCOUNT, POVERTY GAP, SQUARED POVERTY GAP AND WATTS

	Headcount (P0)			Poverty gap (P1)			Squared poverty gap (P2)			Watts (W)		
	Full model	Rest. model (only initial cond.)	Rest. model (only income)	Full model	Rest. model (only initial cond.)	Rest. model (only income)	Full model	Rest. model (only initial cond.)	Rest. model (only income)	Full model	Rest. model (only initial cond.)	Rest. model (only income)
Initial income (log)	0.09*** (0.02)	0.01*** (0.00)	0.05*** (0.01)	0.05*** (0.01)	0.01** (0.00)	0.04*** (0.01)	0.03** (0.01)	0.00 (0.00)	0.03** (0.01)	0.05** (0.01)	0.01** (0.00)	0.04*** (0.01)
Annual income growth	3.72*** (0.65)		2.02*** (0.32)	2.65*** (0.47)		2.14*** (0.37)	1.84*** (0.43)		1.86*** (0.44)	2.74*** (0.48)		2.07*** (0.35)
Initial Gini index	-0.31*** (0.06)	-0.07*** (0.02)		-0.16*** (0.04)	-0.05** (0.02)		-0.10** (0.05)	-0.04 (0.03)		-0.19*** (0.05)	-0.06** (0.02)	
Annual Gini index change	-3.77*** (1.01)			-2.36*** (0.86)			-1.31 (0.96)			-2.04** (0.84)		
μ_1	0.33 (1.71)	-2.74*** (1.01)	6.65*** (1.20)	-0.28 (1.75)	-2.78*** (1.04)	5.11*** (1.18)	-0.55 (2.32)	-2.79** (1.29)	3.78*** (1.38)	-1.09 (1.76)	-2.97*** (1.05)	4.98*** (1.11)
μ_2	2.64 (1.78)	-2.06** (1.00)	8.06*** (1.30)	3.40* (1.86)	-1.51 (1.01)	7.96*** (1.43)				2.49 (1.83)	-1.73* (1.01)	7.70*** (1.36)
μ_3	5.59*** (1.91)	-1.39 (0.99)	9.65*** (1.47)									
N	98	98	98	100	100	100	100	100	100	100	100	100
Pseudo-R2	0.66	0.11	0.46	0.60	0.06	0.50	0.53	0.03	0.49	0.61	0.06	0.48

Notes: The table shows the estimated results of the ordered logit models in Equations (3)-(5) for the headcount, 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 6. DOMINANCE STATISTICS OF THE FULL MODEL

	Headcount (P0)	Poverty gap (P1)	Squared poverty gap (P2)	Watts (W)
Initial income (log)	0.26	0.19	0.09	0.19
Annual income growth	0.28	0.35	0.40	0.34
Initial Gini index	0.09	0.05	0.03	0.06
Gini index change	0.02	0.02	0.02	0.01
Pseudo-R2	0.66	0.60	0.53	0.61

Notes: The table reports the dominance statistics of the full model in Equation (3), 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.

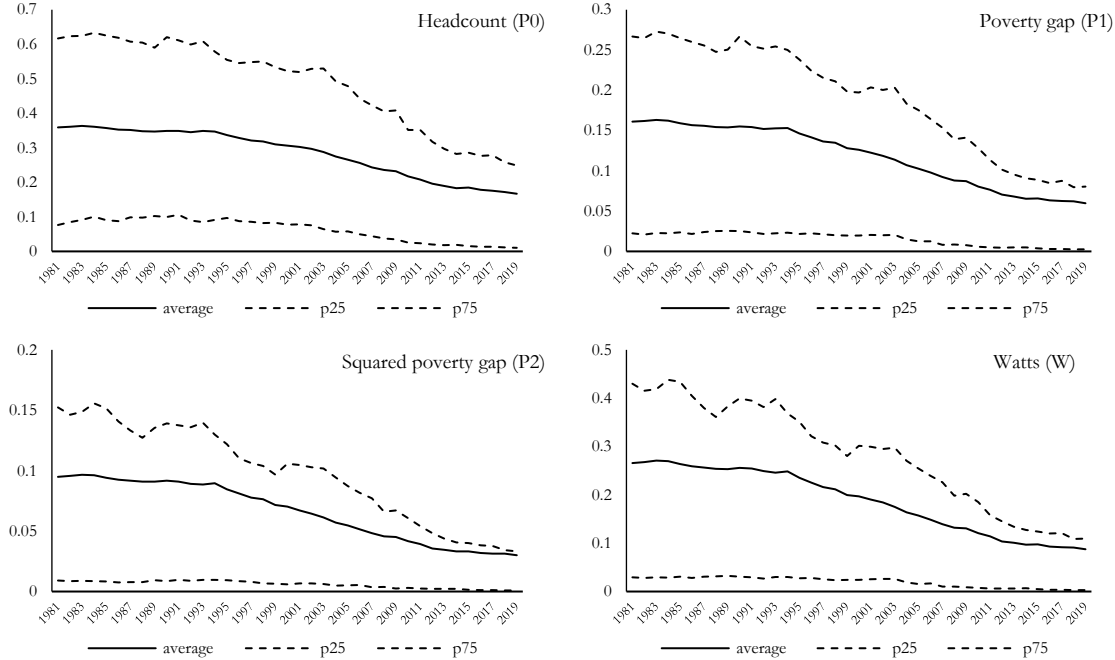
TABLE 7. CONFUSION MATRICES BY CLUB. HEADCOUNT, POVERTY GAP, SQUARED POVERTY GAP AND WATTS

<i>Full model vs Actual membership</i>						
		Full model				
Actual membership		Club 1	Club 2	Club 3	Club 4	Total
Headcount (P0)	Club 1	83% (19)	9% (2)	9% (2)	0% (0)	100% (23)
	Club 2	25% (3)	33% (4)	42% (5)	0% (0)	100% (12)
	Club 3	0% (0)	38% (5)	46% (6)	15% (2)	100% (13)
	Club 4	0% (0)	0% (0)	2% (1)	98% (49)	100% (50)
Poverty gap (P1)	Club 1	65% (11)	29% (5)	6% (1)		100% (17)
	Club 2	17% (4)	70% (16)	13% (3)		100% (23)
	Club 3	0% (0)	3% (2)	97% (58)		100% (60)
Squared poverty gap (P2)	Club 1	65% (13)	35% (7)			100% (20)
	Club 2	4% (3)	96% (77)			100% (80)
Watts (W)	Club 1	63% (12)	37% (7)	0% (0)		100% (19)
	Club 2	22% (5)	65% (15)	13% (3)		100% (23)
	Club 3	0% (0)	3% (2)	97% (56)		100% (58)
<i>Restricted model (only initial conditions) vs Actual membership</i>						
		Initial conditions only				
Actual membership		Club 1	Club 2	Club 3	Club 4	Total
Headcount (P0)	Club 1	48% (11)	0% (0)	0% (0)	52% (12)	100% (23)
	Club 2	17% (2)	0% (0)	0% (0)	83% (10)	100% (12)
	Club 3	54% (7)	0% (0)	0% (0)	46% (6)	100% (13)
	Club 4	8% (4)	0% (0)	0% (0)	92% (46)	100% (50)
Poverty gap (P1)	Club 1	18% (3)	0% (0)	82% (14)		100% (17)
	Club 2	4% (1)	0% (0)	96% (22)		100% (23)
	Club 3	3% (2)	0% (0)	97% (58)		100% (60)
Squared poverty gap (P2)	Club 1	0% (0)	100% (20)			100% (20)
	Club 2	0% (0)	100% (80)			100% (80)
Watts (W)	Club 1	21% (4)	0% (0)	79% (15)		100% (19)
	Club 2	9% (2)	0% (0)	91% (21)		100% (23)
	Club 3	5% (3)	0% (0)	95% (55)		100% (58)
<i>Restricted model (only income) vs Actual membership</i>						
		Income only				
Actual membership		Club 1	Club 2	Club 3	Club 4	Total
Headcount (P0)	Club 1	78% (18)	4% (1)	9% (2)	9% (2)	100% (23)
	Club 2	58% (7)	17% (2)	17% (2)	8% (1)	100% (12)
	Club 3	8% (1)	23% (3)	38% (5)	31% (4)	100% (13)
	Club 4	0% (0)	0% (0)	6% (3)	94% (47)	100% (50)
Poverty gap (P1)	Club 1	59% (10)	35% (6)	6% (1)		100% (17)
	Club 2	13% (3)	65% (15)	22% (5)		100% (23)
	Club 3	0% (0)	7% (4)	93% (56)		100% (60)
Squared poverty gap (P2)	Club 1	65% (13)	35% (7)			100% (20)
	Club 2	5% (4)	95% (76)			100% (80)
Watts (W)	Club 1	63% (12)	32% (6)	5% (1)		100% (19)
	Club 2	17% (4)	57% (13)	26% (6)		100% (23)
	Club 3	0% (0)	5% (3)	95% (55)		100% (58)

Notes: The table reports the predictive performance for each club of the ordered logit models in Equations (3)-(5) for the headcount, 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) method. 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.

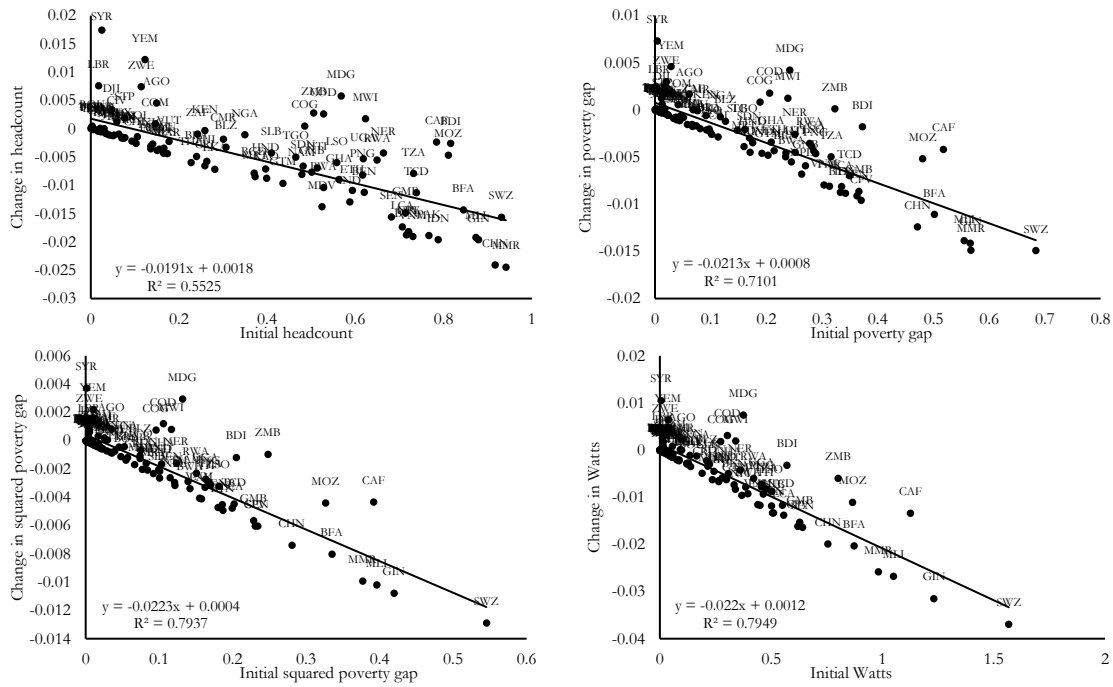
FIGURES

FIGURE 1. ABSOLUTE POVERTY TRENDS



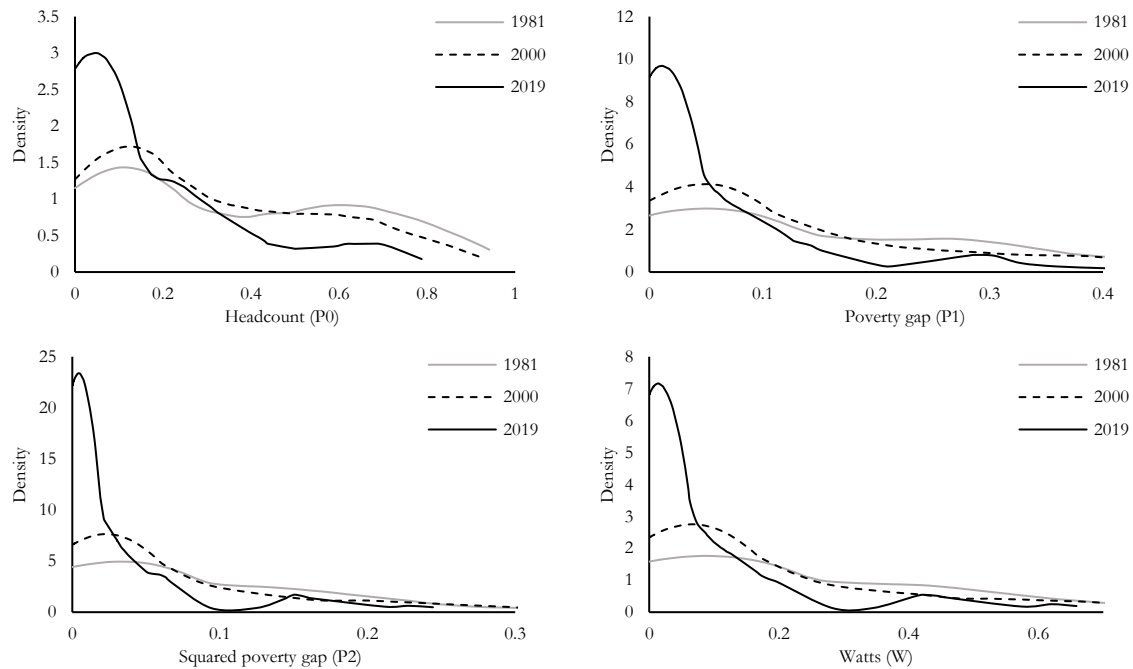
Note: The figures show the time path of the cross-sectional average and 25th and 75th percentiles of each poverty measure for the sample of 100 emerging and developing countries over the period 1981-2019.

FIGURE 2. ABSOLUTE POVERTY. BETA CONVERGENCE



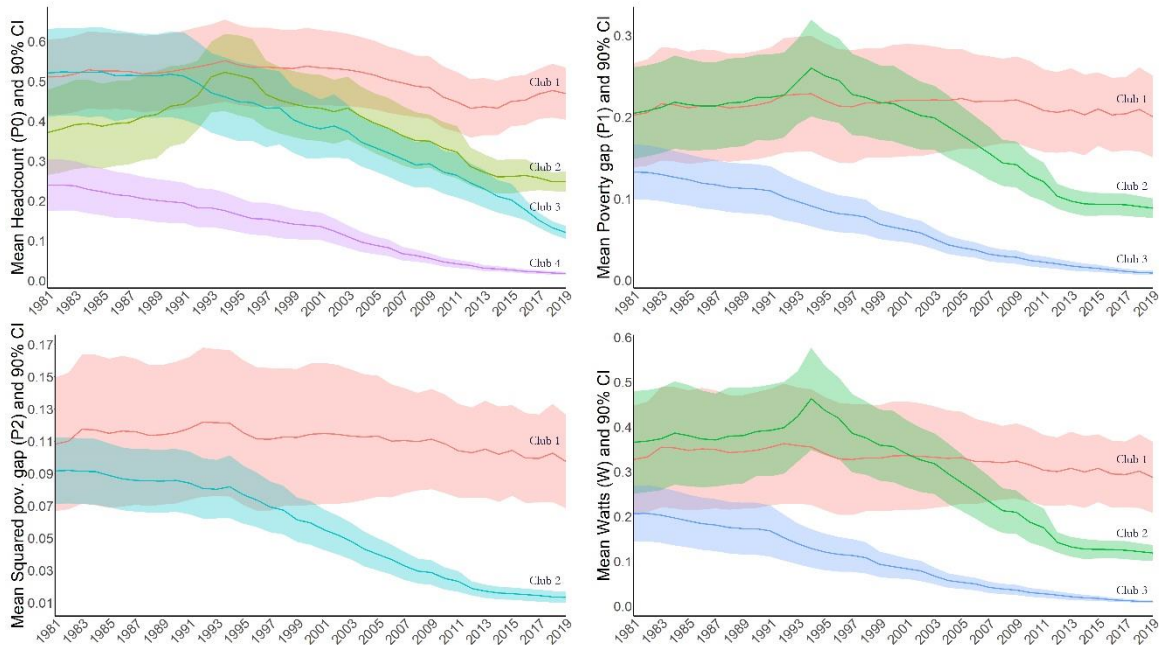
Note: The figures show, for the sample of 100 emerging and developing countries, standard β -convergence graphs for the different poverty measures, that is, the relationship between the annual change in poverty (in p.p.) between 1981 and 2019 and its initial level (in 1981).

FIGURE 3. POVERTY DISTRIBUTIONS AT INITIAL, MIDDLE AND FINAL PERIOD



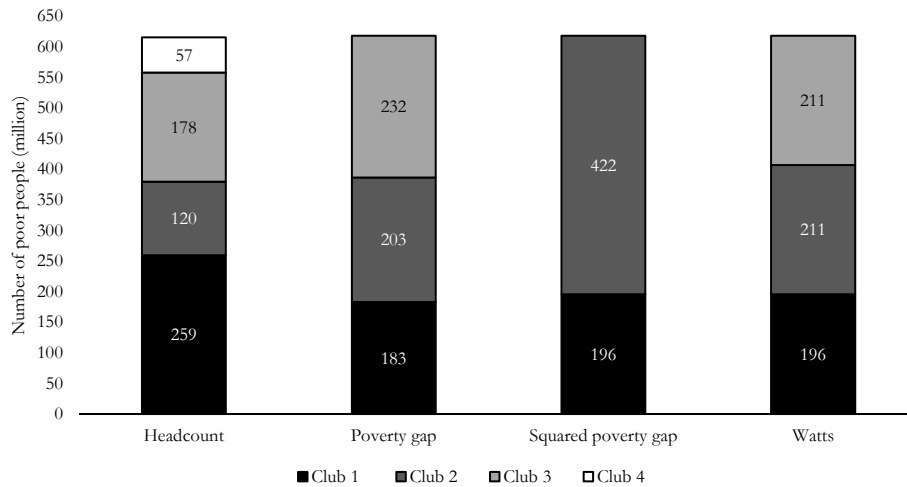
Note: The figures show the cross-country distribution of each poverty measure at the beginning (1981), middle (2000), and end (2019) of the sample period.

FIGURE 4. ABSOLUTE POVERTY TRENDS BY CONVERGENCE CLUB



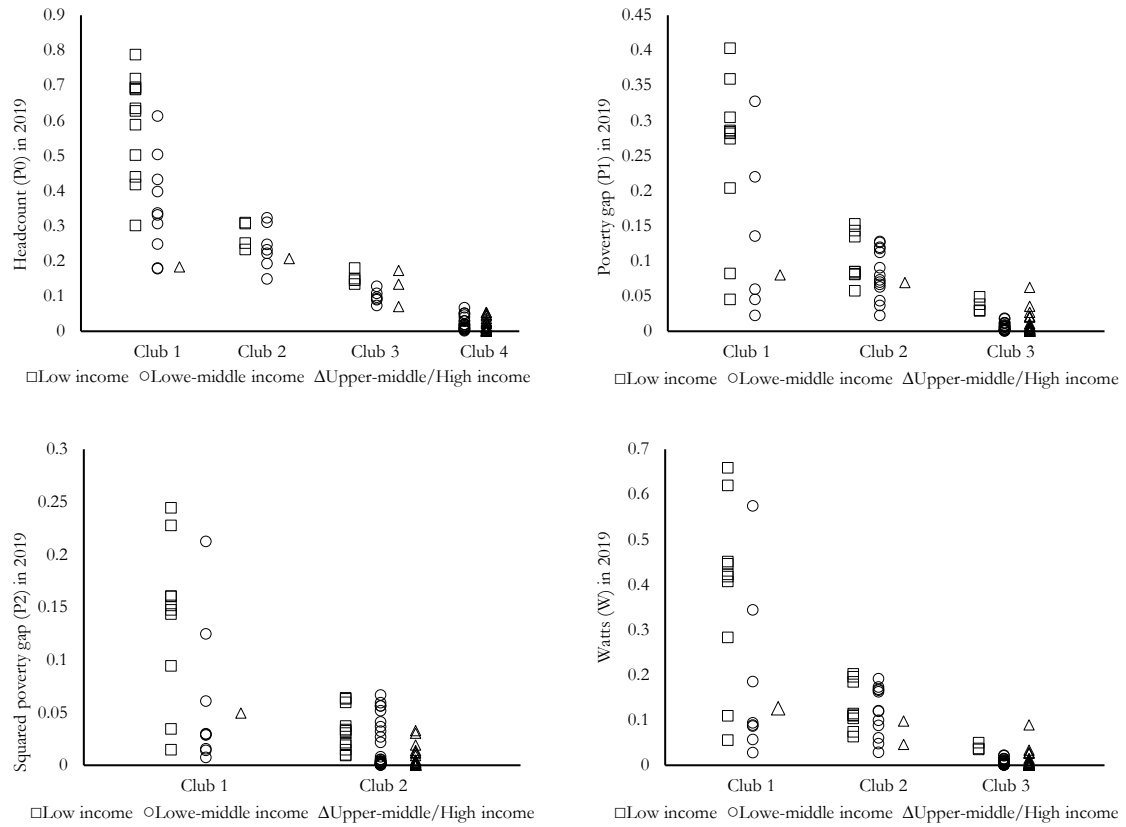
Note: The figures show the time path of the cross-sectional average of each poverty measure and year, and for each poverty club between 1981 and 2019, along with the 90% confidence intervals.

FIGURE 5. TOTAL NUMBER OF POOR IN 2019, BY POVERTY CLUB



Notes: The figure shows how the world's poor were allocated in 2019 across poverty clubs. For each country, we multiply its headcount poverty rate by its 2019 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 6. POVERTY CLUBS, WORLD BANK'S INCOME GROUPS AND POVERTY LEVELS IN 2019



Notes: In the figures, the vertical axis measures the 2019 poverty rate of each country, with countries grouped by poverty club along the horizontal axis. The symbols (square, circle and triangle) denote the classification of each country according to the World Bank income classification for 2019: high and upper-middle income (combined in the figure into a single group), lower-middle income, and low income.

APPENDIX A. ABSOLUTE POVERTY MEASURES AND POVERTY CONVERGENCE CLUBS

TABLE A1. ABSOLUTE POVERTY MEASURES: INITIAL AND FINAL PERIOD

Reg.	Country	ISO3	1981				2019				Population (2019, million)
			P0	P1	P2	W	P0	P1	P2	W	
MNA	Algeria	DZA	2.61	0.18	0.02	0.23	0.32	0.12	0.10	0.09	42.71
SSA	Angola	AGO	15.65	6.47	3.68	10.47	32.27	12.59	6.65	19.15	32.35
SAS	Bangladesh	BGD	39.81	10.14	3.69	13.27	7.23	1.19	0.32	1.40	165.52
LAC	Belize	BLZ	31.50	13.09	7.70	21.79	18.26	8.03	4.95	12.64	0.39
SSA	Benin	BEN	62.19	23.68	11.59	33.71	19.24	4.52	1.57	5.65	12.29
SAS	Bhutan	BTN	71.39	33.19	18.54	50.36	0.34	0.06	0.02	0.07	0.77
LAC	Bolivia	BOL	16.18	8.56	5.80	14.75	1.92	0.60	0.28	0.79	11.78
SSA	Botswana	BWA	49.69	22.38	12.68	35.60	13.37	3.52	1.39	4.62	2.50
LAC	Brazil	BRA	24.43	9.86	5.66	12.69	5.39	2.11	1.16	2.74	211.78
ECA	Bulgaria	BGR	0.07	0.06	0.06	0.00	0.92	0.35	0.18	0.50	6.98
SSA	Burkina Faso	BFA	82.79	47.96	31.35	81.91	30.03	8.05	3.04	10.32	20.95
SSA	Burundi	BDI	82.98	38.76	21.66	59.97	71.86	30.41	16.04	45.09	11.88
SSA	Cabo Verde	CPV	71.38	36.55	22.66	60.96	2.85	0.58	0.19	0.71	0.58
SSA	Cameroon	CMR	24.93	6.59	2.49	8.43	23.15	7.28	3.22	9.94	25.78
SSA	Central African Rep.	CAF	76.81	50.05	37.56	107.53	69.39	35.89	22.75	61.97	5.21
SSA	Chad	TCD	73.66	34.74	20.04	54.67	30.88	8.43	3.26	10.94	16.13
LAC	Chile	CHL	14.87	5.03	2.69	7.55	0.58	0.34	0.27	0.30	19.04
EAP	China	CHN	89.52	43.76	25.13	68.57	0.14	0.03	0.01	0.03	1407.75
LAC	Colombia	COL	10.62	5.16	3.96	3.62	5.29	2.05	1.23	2.63	50.19
SSA	Comoros	COM	13.80	3.79	1.51	5.06	17.93	6.27	2.97	8.88	0.79
SSA	Congo, Dem. Rep.	COD	54.56	21.61	11.18	31.96	62.72	27.36	15.16	42.23	89.91
SSA	Congo, Rep.	COG	38.96	13.57	6.39	19.00	50.25	21.95	12.46	34.39	5.57
LAC	Costa Rica	CRI	27.02	12.06	7.17	20.66	1.06	0.42	0.25	0.48	5.09
SSA	Cote d'Ivoire	CIV	6.48	1.92	1.01	3.17	10.70	2.23	0.72	2.76	26.15
MNA	Djibouti	DJI	4.85	1.22	0.49	1.63	17.73	5.94	2.88	8.66	1.07
LAC	Dominican Republic	DOM	6.72	2.22	1.13	2.90	0.83	0.23	0.13	0.21	10.88
LAC	Ecuador	ECU	16.25	7.34	4.70	11.92	3.58	1.09	0.50	1.47	17.34
MNA	Egypt, Arab Rep.	EGY	12.26	2.00	0.51	2.33	1.92	0.31	0.09	0.39	105.62
LAC	El Salvador	SLV	18.05	10.88	10.11	7.71	1.40	0.28	0.09	0.34	6.28
SSA	Eswatini	SWZ	93.26	68.81	55.01	158.36	33.65	11.75	5.62	16.62	1.17
SSA	Ethiopia	ETH	58.70	20.97	9.81	29.26	17.89	4.88	1.90	6.32	114.12
EAP	Fiji	FJI	4.19	0.73	0.21	0.87	1.06	0.15	0.04	0.17	0.92
SSA	Gabon	GAB	2.70	0.58	0.22	0.75	2.47	0.58	0.23	0.78	2.24
SSA	Gambia, The	GMB	72.86	38.05	23.99	65.78	14.95	3.82	1.46	4.94	2.51
SSA	Ghana	GHA	62.98	24.62	12.59	36.84	22.13	7.92	4.10	12.04	31.52
LAC	Guatemala	GTM	45.72	21.64	13.04	36.57	6.99	2.01	0.91	2.77	16.60
SSA	Guinea	GIN	87.88	56.63	41.96	123.16	13.36	2.93	0.98	3.67	12.88
SSA	Guinea-Bissau	GNB	49.15	26.41	18.15	49.01	20.99	4.51	1.45	5.52	1.97
LAC	Haiti	HTI	53.20	26.38	17.02	48.84	25.02	8.14	3.72	11.38	11.16
LAC	Honduras	HND	40.03	17.76	10.05	28.48	12.74	4.30	2.17	6.02	9.96
SAS	India	IND	58.08	18.80	8.11	25.76	9.66	1.79	0.54	2.17	1383.11
EAP	Indonesia	IDN	77.78	33.32	17.42	49.52	4.38	0.57	0.12	0.65	269.58
MNA	Iran, Islamic Rep.	IRN	9.02	2.26	0.84	2.92	1.01	0.20	0.07	0.26	86.56
MNA	Iraq	IRQ	0.49	0.04	0.01	0.05	0.02	0.00	0.00	0.00	41.56
LAC	Jamaica	JAM	5.16	1.42	0.69	1.76	1.11	0.24	0.07	0.29	2.81
SSA	Kenya	KEN	26.64	9.51	4.70	14.03	24.72	6.96	2.91	9.38	50.95
EAP	Kiribati	KIR	7.88	1.99	0.77	2.61	1.81	0.32	0.09	0.38	0.12
EAP	Korea, Rep.	KOR	3.00	1.01	0.55	1.68	0.23	0.05	0.01	0.06	51.77
EAP	Lao PDR	LAO	38.02	9.18	3.25	11.59	6.62	1.06	0.29	1.26	7.21
SSA	Lesotho	LSO	55.13	28.07	17.80	49.43	33.04	11.91	5.91	17.30	2.23
SSA	Liberia	LBR	1.76	0.75	0.41	1.21	30.57	8.46	3.36	11.06	4.99
SSA	Madagascar	MDG	59.72	25.98	14.36	40.53	78.75	40.27	24.43	65.88	27.53
SSA	Malawi	MWI	62.94	24.40	12.01	34.97	69.06	28.55	14.74	41.73	18.87
EAP	Malaysia	MYS	4.15	0.87	0.30	1.11	0.01	0.00	0.00	0.00	32.80

SAS	Maldives	MDV	48.71	15.69	6.94	21.46	0.00	0.00	0.00	0.00	0.51
SSA	Mali	MLI	89.02	58.57	42.70	113.50	14.45	2.87	0.90	3.51	20.57
SSA	Mauritania	MRT	39.60	17.12	9.93	28.59	5.12	1.16	0.41	1.45	4.38
SSA	Mauritius	MUS	14.71	3.38	1.20	4.29	0.08	0.01	0.00	0.01	1.27
LAC	Mexico	MEX	7.02	1.85	0.74	2.45	2.70	0.80	0.38	1.04	125.09
EAP	Mongolia	MNG	12.95	2.78	0.88	3.39	0.59	0.08	0.02	0.09	3.23
MNA	Morocco	MAR	15.92	3.92	1.33	5.10	0.67	0.11	0.03	0.14	36.30
SSA	Mozambique	MOZ	83.49	51.13	35.54	94.28	63.40	28.38	16.00	44.56	30.29
EAP	Myanmar	MMR	93.60	55.32	36.26	94.63	1.17	0.18	0.05	0.21	53.04
SSA	Namibia	NAM	48.45	24.02	14.34	39.54	17.28	6.21	3.05	8.91	2.45
SAS	Nepal	NPL	73.16	27.13	12.61	38.09	2.84	0.55	0.16	0.66	28.83
LAC	Nicaragua	NIC	19.43	5.76	2.53	7.97	3.93	0.85	0.32	1.09	6.66
SSA	Niger	NER	66.86	25.48	12.56	36.67	50.07	15.27	6.29	20.18	23.44
SSA	Nigeria	NGA	39.83	14.17	6.62	20.24	30.92	8.99	3.66	11.88	203.30
SAS	Pakistan	PAK	75.23	30.15	14.92	42.99	4.99	0.63	0.13	0.71	223.29
LAC	Panama	PAN	11.86	5.96	4.57	6.00	1.00	0.36	0.21	0.41	4.23
EAP	Papua New Guinea	PNG	62.51	29.38	17.09	46.67	30.56	11.20	5.63	16.26	9.54
LAC	Paraguay	PRY	1.48	0.34	0.18	0.32	1.01	0.19	0.06	0.24	6.53
LAC	Peru	PER	3.35	0.86	0.35	1.20	3.00	0.77	0.32	1.05	32.83
EAP	Philippines	PHL	25.81	6.49	2.17	8.35	4.51	0.77	0.21	0.92	110.38
ECA	Poland	POL	0.21	0.14	0.14	0.02	0.00	0.00	0.00	0.00	37.97
ECA	Romania	ROU	0.30	0.29	0.29	0.00	2.16	0.76	0.45	0.71	19.37
SSA	Rwanda	RWA	65.91	28.48	15.52	43.36	43.90	14.29	6.37	19.57	12.84
SSA	Sao Tome and Principe	STP	7.42	1.24	0.32	1.44	14.81	3.64	1.41	4.76	0.22
SSA	Senegal	SEN	66.22	34.65	22.10	60.59	8.94	1.70	0.53	2.08	16.00
SSA	Seychelles	SYC	3.49	1.00	0.41	1.33	0.45	0.11	0.03	0.13	0.10
EAP	Solomon Islands	SLB	42.93	16.12	8.15	23.73	24.69	6.65	2.67	8.77	0.68
SSA	South Africa	ZAF	25.19	7.36	2.74	9.86	20.64	6.92	3.28	9.80	58.09
SAS	Sri Lanka	LKA	26.98	6.45	2.23	8.07	0.96	0.12	0.02	0.13	21.80
LAC	St. Lucia	LCA	70.48	33.43	19.86	55.36	4.75	2.67	1.90	3.33	0.18
SSA	Sudan	SDN	46.71	16.30	7.82	23.25	23.17	5.71	2.13	7.36	43.23
MNA	Syrian Arab Republic	SYR	4.24	0.70	0.19	0.83	68.78	28.15	14.33	40.72	20.10
SSA	Tanzania	TZA	74.15	32.66	17.71	49.66	43.15	12.76	5.17	16.78	59.87
EAP	Thailand	THA	22.32	5.62	1.87	7.22	0.10	0.03	0.01	0.03	71.31
SSA	Togo	TGO	50.69	18.24	8.63	25.57	27.48	8.17	3.42	10.91	8.24
EAP	Tonga	TON	6.88	2.02	0.90	2.76	1.48	0.30	0.09	0.36	0.11
LAC	Trinidad and Tobago	TTO	0.00	0.00	0.00	0.00	0.21	0.11	0.11	0.02	1.52
MNA	Tunisia	TUN	13.58	3.36	1.24	4.32	0.08	0.01	0.00	0.01	12.05
ECA	Turkiye	TUR	4.77	1.01	0.38	1.25	0.36	0.05	0.01	0.05	83.48
SSA	Uganda	UGA	59.30	26.55	15.15	42.59	41.72	13.41	5.95	18.40	42.95
LAC	Uruguay	URY	2.36	0.50	0.18	0.62	0.10	0.04	0.03	0.04	3.43
EAP	Vanuatu	VUT	17.94	4.62	1.76	5.98	9.22	2.22	0.79	2.80	0.30
EAP	Vietnam	VNM	70.12	27.86	13.75	39.70	0.77	0.15	0.05	0.18	95.78
MNA	Yemen, Rep.	YEM	12.66	2.96	1.06	3.77	58.78	20.36	9.43	28.29	31.55
SSA	Zambia	ZMB	52.01	33.39	25.71	83.14	61.25	32.71	21.22	57.44	18.38
SSA	Zimbabwe	ZWE	11.82	2.16	0.55	2.50	39.76	13.50	6.09	18.51	15.36

Notes: 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.

EAP: East Asia and Pacific; ECA: Europe and Central Asia; LAC: Latin America and Caribbean; MNA: Middle East and North Africa; SAS: South Asia; SSA: South-Saharan Africa.

TABLE A2. POVERTY CONVERGENCE CLUBS, INCOME AND INEQUALITY

Region	Country	ISO3	Poverty convergence club				Income 1981	Income 2019	Gini (Circa 1981)	Gini (Circa 2019)	Annual income growth (%)	Annual Gini Change (p.p)
			P0	P1	P2	W						
MNA	Algeria	DZA	4	3	2	3	9.04	10.37	40.20	27.62	0.36	-0.55
SSA	Angola	AGO	2	2	2	2	9.85	5.30	51.96	51.27	-1.63	-0.04
SAS	Bangladesh	BGD	3	3	2	3	2.76	5.19	25.88	32.39	1.66	0.20
LAC	Belize	BLZ	1	1	1	1	6.43	8.06	60.25	53.26	0.60	-1.17
SSA	Benin	BEN	2	1	1	1	2.39	4.74	38.58	37.81	1.80	-0.05
SAS	Bhutan	BTN	4	3	2	3	1.96	12.96	40.90	37.44	4.97	-0.25
LAC	Bolivia	BOL	4	3	2	3	13.45	19.61	58.16	41.65	0.99	-0.75
SSA	Botswana	BWA	3	3	2	2	3.56	9.35	54.21	53.33	2.54	-0.03
LAC	Brazil	BRA	4	3	2	3	8.44	21.12	57.93	53.49	2.41	-0.12
ECA	Bulgaria	BGR	4	3	2	3	20.20	27.43	23.43	40.27	0.81	0.56
SSA	Burkina Faso	BFA	1	2	2	2	1.44	5.05	48.07	47.35	3.30	-0.03
SSA	Burundi	BDI	1	1	1	1	1.58	2.02	33.33	38.63	0.65	0.25
SSA	Cabo Verde	CPV	4	3	2	3	2.25	10.91	52.50	42.38	4.15	-0.72
SSA	Cameroon	CMR	2	2	2	2	4.58	6.12	44.45	46.64	0.77	0.12
SSA	Central African Rep.	CAF	1	1	1	1	1.74	2.52	61.33	56.24	0.98	-0.32
SSA	Chad	TCD	2	2	2	2	1.83	3.81	39.83	37.50	1.94	-0.16
LAC	Chile	CHL	4	3	2	3	11.83	27.13	56.21	44.44	2.19	-0.39
EAP	China	CHN	4	3	2	3	1.18	14.17	28.16	38.17	6.55	0.26
LAC	Colombia	COL	4	3	2	3	9.93	15.54	51.45	51.34	1.18	0.00
SSA	Comoros	COM	1	2	1	1	8.75	6.64	55.93	45.34	-0.73	-1.06
SSA	Congo, Dem. Rep.	COD	1	1	1	1	2.87	2.34	42.16	42.10	-0.53	-0.01
SSA	Congo, Rep.	COG	1	1	1	1	3.48	3.29	47.33	48.94	-0.15	0.27
LAC	Costa Rica	CRI	4	3	2	3	5.94	25.53	47.50	48.19	3.84	0.02
SSA	Cote d'Ivoire	CIV	3	1	1	1	10.60	5.77	45.53	37.18	-1.60	-0.25
MNA	Djibouti	DJI	1	1	1	1	9.06	5.63	40.00	41.59	-1.25	0.11
LAC	Dominican Republic	DOM	4	3	2	3	13.09	16.47	47.78	41.92	0.61	-0.18
LAC	Ecuador	ECU	4	3	2	3	8.58	15.38	53.37	45.71	1.54	-0.31
MNA	Egypt, Arab Rep.	EGY	4	3	2	3	4.53	6.52	32.00	31.89	0.96	0.00
LAC	El Salvador	SLV	4	3	2	3	9.21	12.95	53.95	38.78	0.90	-0.54
SSA	Eswatini	SWZ	1	2	2	2	0.94	5.89	60.46	54.58	4.83	-0.27
SSA	Ethiopia	ETH	3	3	2	2	2.81	4.44	44.57	34.99	1.21	-0.48
EAP	Fiji	FJI	4	3	2	3	8.83	8.24	38.10	30.71	-0.18	-0.44
SSA	Gabon	GAB	4	3	2	3	11.51	12.34	42.19	38.02	0.18	-0.35
SSA	Gambia, The	GMB	3	3	2	3	2.07	5.27	48.52	35.92	2.46	-0.74
SSA	Ghana	GHA	2	2	2	2	2.41	5.60	35.35	43.52	2.21	0.28
LAC	Guatemala	GTM	3	3	2	3	4.78	10.61	58.26	48.28	2.10	-0.36
SSA	Guinea	GIN	3	3	2	3	1.06	4.46	46.84	29.59	3.79	-0.64
SSA	Guinea-Bissau	GNB	.	1	1	1	3.61	4.26	43.61	34.77	0.44	-0.35
LAC	Haiti	HTI	2	2	2	2	4.10	4.73	59.48	41.10	0.37	-1.67
LAC	Honduras	HND	3	2	2	2	5.60	10.12	59.49	48.17	1.56	-0.38
SAS	India	IND	3	3	2	3	2.40	5.17	32.10	35.73	2.02	0.10
EAP	Indonesia	IDN	4	3	2	3	1.69	7.34	33.46	37.61	3.86	0.12
MNA	Iran, Islamic Rep.	IRN	4	3	2	3	9.63	14.39	47.42	40.94	1.06	-0.20
MNA	Iraq	IRQ	4	3	2	3	8.51	12.58	28.60	29.54	1.03	0.16
LAC	Jamaica	JAM	4	3	2	3	9.82	15.41	43.16	45.46	1.18	0.14
SSA	Kenya	KEN	1	2	1	1	7.17	4.63	57.46	40.78	-1.15	-0.73
EAP	Kiribati	KIR	4	3	2	3	6.87	6.27	36.97	27.83	-0.24	-0.70
EAP	Korea, Rep.	KOR	4	3	2	3	8.98	46.29	31.70	31.41	4.32	-0.03
EAP	Lao PDR	LAO	4	3	2	3	3.23	6.67	34.31	38.80	1.91	0.17
SSA	Lesotho	LSO	1	2	2	2	3.33	4.58	56.02	44.88	0.84	-0.36
SSA	Liberia	LBR	2	2	2	2	13.30	3.71	36.48	35.27	-3.36	-0.14
SSA	Madagascar	MDG	1	1	1	1	2.83	1.69	45.26	42.65	-1.36	-0.14
SSA	Malawi	MWI	1	1	1	1	4.33	2.14	65.76	38.54	-1.86	-1.24
EAP	Malaysia	MYS	4	3	2	3	12.64	33.91	48.63	41.18	2.60	-0.22
SAS	Maldives	MDV	4	3	2	3	2.93	22.61	41.31	29.29	5.38	-0.71
SSA	Mali	MLI	3	3	2	3	1.25	5.01	50.44	36.14	3.65	-0.60
SSA	Mauritania	MRT	4	3	2	3	3.78	6.92	43.94	32.62	1.59	-0.42
SSA	Mauritius	MUS	4	3	2	3	4.61	17.65	35.65	36.76	3.53	0.10
LAC	Mexico	MEX	4	3	2	3	11.00	14.64	48.53	46.71	0.75	-0.05
EAP	Mongolia	MNG	4	3	2	3	5.01	10.22	33.20	32.74	1.88	-0.02
MNA	Morocco	MAR	4	3	2	3	5.12	12.46	39.19	39.55	2.34	0.01
SSA	Mozambique	MOZ	1	1	1	1	1.68	2.96	53.56	54.00	1.49	0.02
EAP	Myanmar	MMR	4	3	2	3	1.06	7.31	38.07	30.70	5.07	-3.69
SSA	Namibia	NAM	3	3	2	3	8.69	10.84	63.32	59.07	0.58	-0.35
SAS	Nepal	NPL	4	3	2	3	1.93	6.66	30.06	32.84	3.27	0.11
LAC	Nicaragua	NIC	4	3	2	3	8.07	11.74	49.06	46.16	0.99	-0.14
SSA	Niger	NER	1	2	2	2	2.17	2.88	36.10	37.28	0.74	0.05

SSA	Nigeria	NGA	2	2	2	2	3.73	3.65	38.68	35.13	-0.06	-0.11
SAS	Pakistan	PAK	4	3	2	3	1.81	4.97	33.32	29.59	2.65	-0.12
LAC	Panama	PAN	4	3	2	3	15.03	33.50	58.91	49.84	2.11	-0.30
EAP	Papua New Guinea	PNG	1	2	2	2	2.48	4.26	45.77	41.85	1.43	-0.30
LAC	Paraguay	PRY	4	3	2	3	14.65	19.46	40.84	45.65	0.75	0.17
LAC	Peru	PER	4	3	2	3	14.37	13.80	45.64	41.56	-0.11	-0.12
EAP	Philippines	PHL	4	3	2	3	4.58	7.24	41.04	37.81	1.21	-0.10
ECA	Poland	POL	4	3	2	3	14.41	20.50	25.17	30.24	0.93	0.15
ECA	Romania	ROU	4	3	2	3	15.51	21.47	23.31	34.80	0.86	0.38
SSA	Rwanda	RWA	1	2	2	2	2.62	3.51	48.55	43.71	0.77	-0.30
SSA	Sao Tome and Principe	STP	2	2	1	2	5.75	5.57	32.13	40.75	-0.08	0.51
SSA	Senegal	SEN	3	3	2	3	2.39	6.02	54.14	38.12	2.43	-0.59
SSA	Seychelles	SYC	4	3	2	3	11.46	22.70	42.78	32.13	1.80	-0.56
EAP	Solomon Islands	SLB	2	2	2	2	3.87	4.18	46.10	37.06	0.20	-1.29
SSA	South Africa	ZAF	2	2	2	2	9.77	11.90	59.33	63.03	0.52	0.18
SAS	Sri Lanka	LKA	4	3	2	3	3.58	9.25	32.47	37.66	2.50	0.15
LAC	St. Lucia	LCA	4	3	2	3	1.98	20.93	42.58	51.23	6.21	0.41
SSA	Sudan	SDN	2	2	2	2	2.74	3.95	35.40	34.24	0.96	-0.23
MNA	Syrian Arab Republic	SYR	1	1	1	1	7.37	2.10	35.17	37.52	-3.31	0.34
SSA	Tanzania	TZA	1	2	2	2	1.85	3.39	35.29	40.49	1.60	0.19
EAP	Thailand	THA	4	3	2	3	5.66	16.04	45.22	34.86	2.74	-0.27
SSA	Togo	TGO	.	1	1	1	3.30	4.61	42.21	42.35	0.88	0.01
EAP	Tonga	TON	4	3	2	3	7.28	8.92	37.69	33.52	0.53	-0.28
LAC	Trinidad and Tobago	TTO	4	3	2	3	27.38	30.50	42.60	40.27	0.28	-0.58
MNA	Tunisia	TUN	4	3	2	3	6.71	14.58	43.43	32.82	2.04	-0.35
ECA	Turkiye	TUR	4	3	2	3	8.66	22.20	43.48	41.91	2.48	-0.05
SSA	Uganda	UGA	1	2	2	2	2.41	3.56	44.36	42.71	1.03	-0.06
LAC	Uruguay	URY	4	3	2	3	14.69	28.78	45.94	39.68	1.77	-0.48
EAP	Vanuatu	VUT	3	2	2	2	4.91	5.52	37.35	32.32	0.31	-0.56
EAP	Vietnam	VNM	4	3	2	3	1.93	14.70	35.66	35.72	5.34	0.00
MNA	Yemen, Rep.	YEM	1	1	1	1	5.45	2.50	35.00	36.71	-2.05	0.11
SSA	Zambia	ZMB	1	1	1	1	3.96	3.02	60.51	57.14	-0.72	-0.14
SSA	Zimbabwe	ZWE	1	1	1	1	7.16	4.50	43.15	50.26	-1.22	0.89

Notes: 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 2017 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.

EAP: East Asia and Pacific; ECA: Europe and Central Asia; LAC: Latin America and Caribbean; MNA: Middle East and North Africa; SAS: South Asia; SSA: South-Saharan Africa.

APPENDIX B. PHILLIPS AND SUL'S STATISTICAL MODEL

To test for club convergence for each of the poverty measures considered, we follow Phillips & Sul (2007) (P-S for short). We assume a generic latent factor model without specifying its origin and its relationship with income or inequality,

$$P_{it} = \delta_{it}\mu_t, \quad (\text{B1})$$

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.¹ 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:

$$p_{it} = \frac{P_{it}}{\frac{1}{N}\sum P_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum \delta_{it}}, \quad (\text{B2})$$

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:

$$\delta_{it} = \delta_i + s_{it}\varepsilon_{it}; \text{ with } s_{it} = \frac{s_i}{L(t)\cdot t^\alpha}; \text{ for } t \geq 1, s_i > 0, \quad (\text{B3})$$

Where s_i is a time-invariant parameter, ε_{it} is an iid standard normal random variable, $L(t)$ 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 .

¹ 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 & Payne, 2019; Johnson & Papageorgiou, 2020).

It is easy to see that under the null hypothesis of convergence $\lim_{t \rightarrow \infty} \delta_{it} = \bar{\delta}_i = \bar{\delta}$ for all i , while under the alternative hypothesis $\lim_{t \rightarrow \infty} \delta_{it} \neq \bar{\delta}$ for at least some i . Using (B3), testing the null of 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 $p_{it} \rightarrow 1$ as $t \rightarrow \infty$ 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)²:

$$\log\left(\frac{\sigma_1^2}{\sigma_t^2}\right) - 2 \ln(\ln(t)) = a + b \ln t + u_t, \quad (\text{B4})$$

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 (B3).

Testing for convergence using equation (B4) 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 (B4) 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 (B4) 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 (B4), 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 & 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.

² See Appendix B in P-S for details.

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 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.³

Table B1 shows the results from the estimation of equation (B4) (i.e., the estimates of b and the associated t-statistics) over the full sample and for each poverty measure and club. The full-sample t-statistics are: -47.5 for P0, -49.1 for P1, -58.4 for P2 and -38.7 for W. Since they are well below the critical level of -1.65, we can reject both absolute and conditional convergence for the full sample and all poverty measures. Next, we apply the clustering algorithm described above and distinguish between club-convergence and diverging units, and obtain four clubs for P0, 3 clubs for P1 and W and 2 clubs for P2.

TABLE B1. ABSOLUTE POVERTY: CONVERGENCE CLUBS

Measure	Club	b	t
Headcount (P0)	Club1	-0.08	-1.01
	Club2	0.02	0.19
	Club3	0.02	0.15
	Club4	0.15	2.13
	Full sample	-1.40	-47.51
Poverty gap (P1)	Club1	0.14	1.39
	Club2	0.19	3.05
	Club3	0.08	0.78
	Full sample	-1.23	-49.11
Squared poverty gap (P2)	Club1	0.17	2.61
	Club2	-0.09	-1.49
	Full sample	-1.03	-58.43
Watts (W)	Club1	0.28	3.86
	Club2	0.05	0.90
	Club3	0.17	2.39
	Full sample	-1.15	-38.69

Note: For each poverty club under each poverty measure, the fourth and fifth columns show the b estimates and associated t-statistics from the $\log-t$ regression (Equation B4).

³The 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 & Metiu (2015) or Schnurbus et al. (2017).

APPENDIX C. CHOICE OF SMOOTHING PARAMETER IN THE P-S APPROACH

In a recent survey, Tomal (2023) emphasizes that the choice of smoothing parameter in the HP filter may have a potentially relevant impact on the P-S estimates. The reason is that, depending on the value of the smoothing coefficient, the filtered time series will capture more or less cyclical variation and/or noise, and will or will not capture certain turning points which could affect countries' club membership. In this appendix, we compare our baseline club convergence results with those obtained using smoothing parameter values of 100 and 400.

In Figure C1 below, we report the time path of the cross-sectional mean for each poverty measure and club under two different values of the smoothing parameter. The graph on the left shows the results obtained using our preferred value of 6.25 (as in the main body of the paper), while the graph on the right shows the results obtained setting the smoothing parameter to 100.

The club configuration remains identical in terms of the number of clubs, except for the Watts index. Under both smoothing parameter values, application of the PS procedure yields 4 headcount poverty clubs, 3 poverty gap clubs, and 2 squared poverty gap clubs. However, when the smoothing parameter is set to 100 instead of 6.25, we find 4, rather than 3, Watts index clubs. The figure suggests that this extra club, which consists of only 12 countries, eventually becomes almost indistinguishable from the lowest-poverty Watts club.

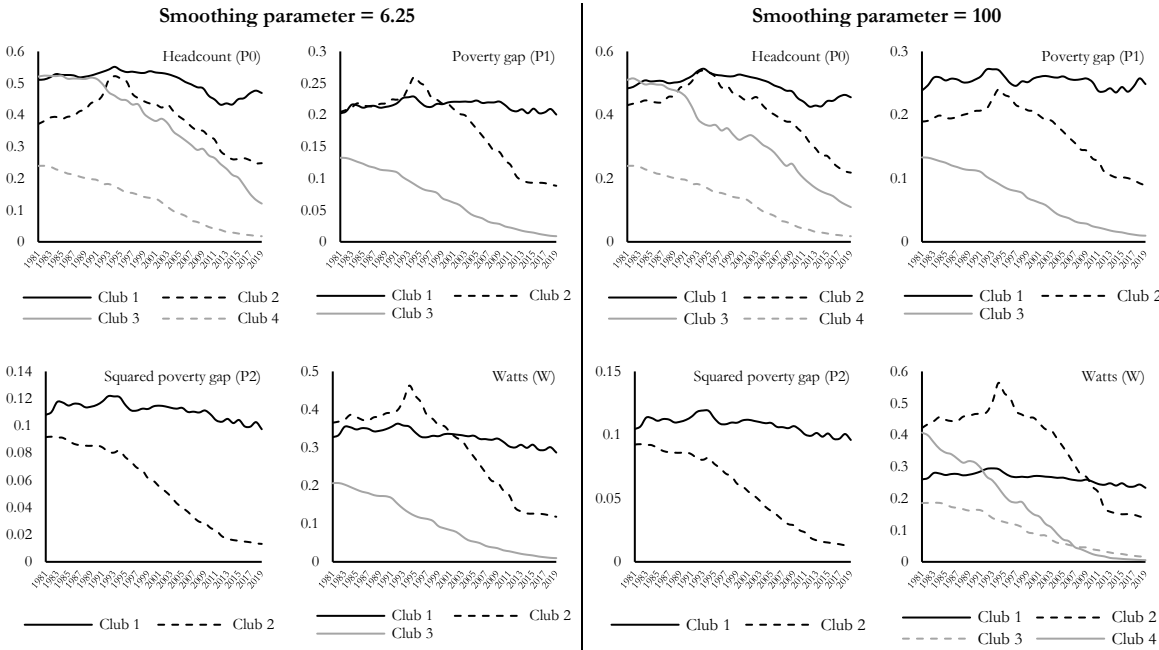
When using the baseline smoothing parameter value of 6.25, the lowest-poverty club found under the Watts index comprises 58 countries. Of these, 56 belong to one of the two lowest-poverty clubs likewise found for the Watts index when setting the smoothing parameter to 100. The latter two clubs combined comprise a total of 60 countries.

In turn, Figure C2 compares our baseline results with those obtained setting the smoothing parameter to 400. As before, the club configuration remains the same as in the baseline except for the Watts index, which yields one extra club. The situation is very similar to the one just described. The same result obtains if the smoothing parameter is allowed to vary in a neighbourhood of 100 or 400.

Overall, club membership is very similar across the three smoothing parameter scenarios considered. Of course, some countries do move from one club to another as the value of the smoothing parameter changes. Heuristically, these countries are close to two adjacent clubs -- i.e., their long-run poverty levels lie between two distributional modes, and thus applying more

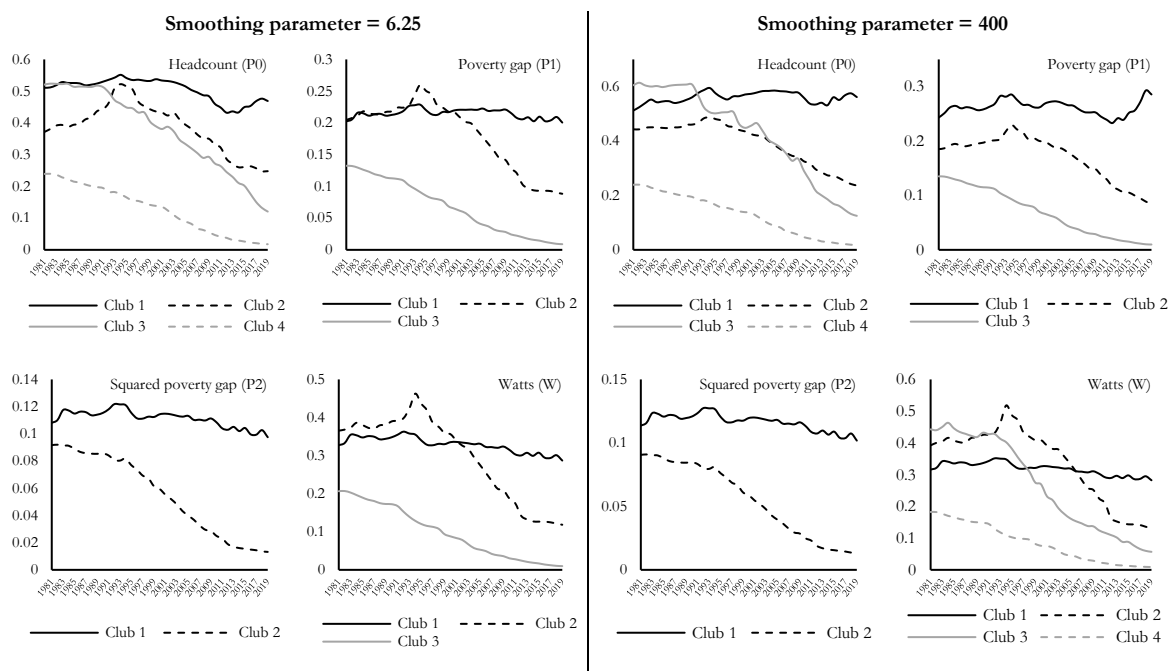
or less smoothing to the series may shift the countries from one club to the next. However, the vast majority of countries remain in the same club regardless of the choice of smoothing parameter: for each poverty measure under analysis, the correlation of countries' club membership (as captured by Spearman's rank correlation coefficient) across the three smoothing parameter values exceeds 85% (Table C1). More precisely, 75% of the countries remain in the same club of headcount poverty, while 91% do in the case of the poverty gap, 98% for the squared poverty gap, and 89% for the Watts index (with Clubs 3 and 4 of the Watts index under smoothing parameter values of 100 or 400 considered as a single club).

FIGURE C1. POVERTY TRENDS BY CONVERGENCE CLUB. 6.25 VS 100 SMOOTHING PARAMETER



Note: The figures show the time path of the cross-sectional average of each poverty measure for each poverty club between 1981 and 2019 for different values of the smoothing parameter.

FIGURE C2. POVERTY TRENDS BY CONVERGENCE CLUB. 6.25 VS 400 SMOOTHING PARAMETER



Note: The figures show the time path of the cross-sectional average of each poverty measure for each poverty club between 1981 and 2019 for different values of the smoothing parameter.

TABLE C1. RANK CORRELATION OF CLUB MEMBERSHIP UNDER DIFFERENT CHOICES OF SMOOTHING PARAMETER

Smoothing parameter	Headcount			Poverty gap			Squared poverty gap			Watts		
	6.25	100	400	6.25	100	400	6.25	100	400	6.25	100	400
6.25	1.00	0.98	0.94	1.00	0.97	0.95	1.00	0.97	0.97	1.00	0.85	0.97
100		1.00	0.95		1.00	0.98		1.00	0.94		1.00	0.85
400			1.00			1.00			1.00			1.00

Note: The table shows, for each poverty measure, Spearman's rank correlation coefficient for club membership across the three smoothing parameters.

APPENDIX D. ASSESSING THE ROLE OF INCOME AND INEQUALITY IN CLUB FORMATION

Let $y_{it}(q)$ denote the income of the q -th percentile of the income distribution. It can be expressed as:

$$y_{it}(q) = \bar{y}_{it} L_{it,q}(q), \quad (\text{D1})$$

where \bar{y}_{it} is mean per capita income, $L_{it}(\cdot)$ denotes the Lorenz curve and $L_{it,q}$ its derivative at the q -th percentile.

Plugging this expression for $y_{it}(q)$ into (D1), we get:

$$P_{it} = \int_0^{P_0} \Omega(\bar{y}_{it} L_{it,q}(q), z) dq. \quad (\text{D2})$$

Under lognormality, which is commonly taken to be a fairly good approximation to the actual distribution of income (see e.g., López & 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.

Next, from this general expression, we obtain a reduced form equation to estimate an ordered logit model relating club membership to initial conditions and changes in mean income and the Gini index. We proceed as follows.

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, 3 for P1 and W and 2 for P2). 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:

$$C_i = \begin{cases} 1, & \text{if } P_i^* \leq \mu_1 \\ 2, & \text{if } \mu_1 < P_i^* \leq \mu_2 \\ \dots \\ N, & \text{if } P_i^* > \mu_{N-1} \end{cases}. \quad (\text{D3})$$

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

$$P_i^* = Z_i + \varepsilon_i, \quad (\text{D4})$$

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.

In our case, $Z_i = \beta_1 \log y_{it_0} + \varphi_1 G_{it_0} + \beta_2 \Delta \log y_i + \varphi_2 \Delta G_i$, and plugging this into (D4), we obtain (3), which is a reduced form of P_i^* .

We assume the error terms in (3)-(5) follow a logistic distribution, and estimate the parameters of the above equations and the thresholds μ_j in (D3) 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 ,

$$Pr(C_i = c) = \frac{\exp(Z_i - \mu_{c-1})}{1 + \exp(Z_i - \mu_{c-1})}, \quad (D5)$$

Where $c \in \{1,2,3,4\}$ for P0, $c \in \{1,2,3\}$ for P1 and W and $c \in \{1,2\}$ for P2⁴.

⁴ It should be noted that for P2, estimating an ordered logit model with only two categories (two clubs) is identical to estimating a binomial logit model. In this case, the constant aligns with the thresholds in Equation D3.

APPENDIX E. PREDICTING CLUB MEMBERSHIP FOR THE FULL SAMPLE

Here, we show the full-sample predictive accuracy of the full model (3) as well as the restricted specifications (4)-(5). It is important to note that the predictive accuracy of each model for every poverty measure is given by the values on the main diagonal of the confusion matrices displayed in Table 7. 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 E1 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 80 and 90 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 73 to 89 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.

TABLE E1. PREDICTIVE ACCURACY OF THE ESTIMATED ORDERED LOGIT MODELS

	Headcount (P0)	Poverty Gap (P1)	Squared poverty gap (P2)	Watts (W)
Full model	80% (78)	85% (85)	90% (90)	83% (83)
Restricted model (only initial conditions)	58% (57)	61% (61)	80% (80)	59% (59)
Restricted model (only income)	73% (72)	81% (81)	89% (89)	80% (80)

Notes: The table reports the overall predictive performance of the ordered logit models in Equations (3)-(5) 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 & Sul's (2007) method. 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.