The Future of Global Poverty in a Multi-Speed World

New Estimates of Scale and Location, 2010–2030

Peter Edward and Andy Sumner

Abstract

The data available for assessing the current status and trends of global poverty has significantly improved. And yet serious contentions remain. At the same time, a set of recent papers has sought to use these datasets to make poverty projections. Such projections have significant policy implications because they are used to inform debates on the future scale, nature, and objectives of international aid. Unfortunately, those papers have not yielded a consistent picture of future (and even current) global poverty even though their estimates are all derived from the same basic (PPP and distribution) datasets. In this paper we introduce a new model of growth, inequality and poverty. This new model allows for systematic, methodologically transparent, comparative analyses of estimates of poverty in the future based on a range of different methods. We use the model to explore how estimates of the scale and location of future poverty varies by approach.

JEL Codes: I32, D63

Keywords: poverty, inequality, projections, methodology.

Center for Global Development
www.cgdev.org

Working Paper 327
June 2013

The Future of Global Poverty in a Multi-Speed World: New Estimates of Scale and Location, 2010–2030

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Many thanks for important comments on earlier drafts to the anonymous reviewers and to Ben Leo, Simon Maxwell, Laurence Chandy, Alex Cobham, David Steven, and Charles Kenny.

CGD is grateful to its funders and board of directors for support of this work.

Peter Edward and Andy Sumner . 2013. "The Geography of Global Poverty to 2025 and Beyond: Projections and Pitfalls." CGD Working Paper 327. Washington, DC: Center for Global Development.
http://www.cgdev.org/publication/geography-global-poverty

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Glossary

DRC	Democratic Republic of the Congo
GDP	Gross Domestic Product
GNI	Gross National Income
GrIP	Growth, Inequality and Poverty
HFC	Household Final Consumption
HIC	high-income country
ICP	International Comparison Program
IMF	International Monetary Fund
LDC	Least Developed Country
LIC	low-income country
LMIC	lower middle-income country
MIC	middle-income country
NA	National Account
NA/S	National Account mean to survey mean
pa	per annum
pc	per capita
PPP	Purchasing power parity
S	survey
UMIC	upper middle-income country
UNU	United Nations University
WDI	World Development Indicators
WEO	World Economic Outlook
WIID	World Income Inequality Database

Executive summary

Various recent papers have sought to make projections about the scale and locations of global poverty. Such forecasts have significant policy implications because they are used to inform debates on the scale, nature and objectives of international aid. However, these papers have produced some very different projections for global poverty so that a complex and rather inconsistent picture has emerged. Estimating even current global poverty levels is problematic for a range of reasons arising largely from the limitations of available data and the various alternative modelling approaches used to compensate for these. Forecasts for future poverty become further complicated by the range of scenarios for future economic growth and changes in inequality. Largely as a result of these differences, different analysts arrive at very different understandings of the extent and prospects for global poverty.

In response to this, we introduce here a new model of growth, inequality and poverty that has been developed to allow comparative analyses using a wide range of different input assumptions. We use the model to explore and expose how, and by how much, forecasts of both the scale and location of future poverty vary depending on the modelling approaches and assumptions adopted. We find that: (i) it is plausible that $1.25 and $2 global poverty will reduce substantially by 2030 and the former – $1.25 poverty – could be very low by that time. However, this depends on economic growth and inequality trends; (ii) it is startling just how much difference changes in inequality could make to the future of global poverty – to both the numbers of poor people and the costs of ending poverty. The difference between poverty estimated on current inequality trends versus a hypothetical return to 'best ever' inequality for every country could be up to almost an extra billion $2 poor people in one scenario; (iii) where the world's poor will be located is dependent on changes in inequality to a certain extent as well as the methods used to estimate poverty. We find surprisingly little in the way of compelling evidence that aid should be refocused entirely on low-income fragile states on the basis that global poverty will be based in such countries. Further, we find that even the long (OECD) list of fragile states (low and middle income) would only account for the vast bulk of global poverty in a minority of scenarios. Instead, we argue that it might be more useful to inform policy with an understanding of the range of possible outcomes across a greater variety of potentially relevant country categories.

1. Introduction

The data available for assessing the current status and trends of global poverty has significantly improved. And yet serious contentions remain. At the same time, various recent papers have sought to use these datasets to make poverty projections (e.g. Dercon and Lea, 2012; Hillebrand, 2009; Karver et al., 2012; Kharas and Rogerson, 2012; Ravallion, 2012, 2013). Such projections have significant policy implications because they are used to inform debates on the future scale, nature and objectives of overseas development assistance. Unfortunately, such papers have not yielded a consistent picture of future (and even current) global poverty even though their estimates are all derived from the same basic (PPP and distribution) datasets. In other words, the differences therefore are predominantly methodological.

In this paper we present a new model of growth, inequality and poverty, the GrIP ('Gr'owth, 'I'nequality and 'P'overty) model v1.0. The GrIP model has been deliberately developed to make systematic, methodologically transparent, comparative analyses based on a range of different modelling assumptions in order to ascertain the range of potential outcomes for the evolution of global poverty to 2030. We demonstrate that reliance on one particular approach to make decisions on the future of development aid could be prove to be quite misleading and therefore that recognition of the significance of uncertainties is essential.

The paper is structured as follows: Section 2 discusses recent literature on projections of poverty. Section 3 outlines the GrIP model. Section 4 provides a range of estimates from the GrIP model, under various scenarios and modelling assumptions. Section 5 concludes.

2. Estimating global poverty

2.1. Points of departure

At the outset it is important to recognise that the estimation of global poverty remains contentious. Strident debates exist about the comparability of national surveys of consumption, or income, distribution. Even when surveys purport to address the same measure, differences in survey design and in sample selection can make it difficult to compare one country's survey results with another's. Meanwhile recurring systematic biases (notably that it is notoriously difficult to survey accurately the richest elements in a society) call into question the validity of *all* distribution surveys.

Further, if, as is generally the case when making global estimates, absolute poverty is defined as living below a nominal poverty line (typically some variant of the World Bank's oft-cited dollar-a-day poverty line) it is necessary to convert national currencies into international currencies. The latest revision of the International Comparison Program (ICP) attempted to rectify some of the problems but it has faced extensive criticism (e.g. Deaton, 2010, 2011; Deaton and Heston, 2010; Klasen, 2010). These uncertainties are so substantial that it has even been argued that the practical difficulties of the ICP make international comparisons hazardous (Deaton, 2010).[1] Faced with such intransigent difficulties (even before embarking on debates about what might be a reasonable global poverty line or deciding how to deal with countries not covered by surveys) one might be inclined to give up on all attempts to estimate global poverty and inequality. Despite all the uncertainties there is still benefit in using the available data to attempt to estimate global poverty counts as long as one's approach recognises these uncertainties as Deaton – a prominent critic of the ICP – concludes:

> PPPs for the poorer countries in Africa or in Asia may be *good enough* [emphasis added] to support global poverty counts, at least *provided the uncertainties are recognized* [emphasis added]. (Deaton, 2010, p. 31).

Thus, our paper responds to Deaton's call for a greater recognition of the significance of uncertainties in the building of a new model which seeks to bring to light systematically, those uncertainties.

2.2. Literature review

A set of recent papers have sought to project poverty. One of the most straight-forward is that of Ravallion (2012, 2013) who makes poverty projections for global $1.25 poverty in 2017 and 2022 based on the assumption that the 'recent success against extreme poverty is maintained' (2012, p. 25 and p. 7 respectively). This is done (a) by making a simple linear projection based on the rate of reduction of poverty between 1990 and 2010 (which is labelled an 'optimistic trajectory') and (b) by applying World Bank country-level growth forecasts and assuming mean consumption of households grows in line with GDP growth with no increase in intra-country inequality (an 'ambitious trajectory').

In Ravallion (2013) these projections are taken slightly further. The same 'optimistic' trajectory is used and it is noted that $1.25 poverty on such a linear trajectory would be ended by 2025–2030 with 2027 'as the most likely date' (p. 13). The author notes '[t]his assumes that the robust linear path we have seen for the poverty rate over time will be maintained. That will not be easy'. Ravallion (2013) also adds a third 'pessimistic trajectory' which is the (slow) rate of progress of poverty reduction in the developing world outside

1 There are various issues related to ICP data quality such as: the treatment of urban and rural areas of large countries; prices for 'comparison resistant items' (e.g. government services, health and education); the effects of the regional structure of the latest ICP; the absence of weights within basic headings (which may result in basic headings being priced using high-priced, unrepresentative goods that are rarely consumed in some countries); and the use of national accounts statistics data that does not reflect consumption patterns of people who are poor by global standards (Deaton, 2010).

China in the 1980s and 1990s. In this trajectory ending $1.25 poverty would take 50 years or so.[2]

A different approach is to explore trends across a wider range of growth scenarios using different growth rates for each country and static inequality (see Karver et al., (2012). In these studies, growth rates are derived from scenarios earlier developed by Moss and Leo (2011) on the following kind of pattern:[3]

- Optimistic scenario: assume average national growth rate in World Economic Outlook (WEO) is sustained to whatever point in the future;
- Moderate scenario: as 'Optimistic' minus 1% (based on the historic error of IMF projections – see Aldenhoff, 2007);
- Pessimistic scenario: 50% of 'Optimistic' growth.

Karver et al. (2012) presents the results of this forecasting exercise. The paper projects $1.25 and $2 poverty in 2030 in the following ranges respectively: 230m–680m and 550m–1.6bn (and estimates are also made for a number of non-income poverty indicators).

The forecasts above all use the same World Bank's PovcalNet dataset, where consumption distributions from national surveys are multiplied by means (average per capita consumption or income in PPP $) derived from those same surveys. There are additionally various papers that make poverty projections using models that apply National Account (NA) means, such as GDP or household consumption per capita in PPP $, directly to the survey distributions.[4] Kharas and Rogerson (2012) for example, take IMF growth projections to 2016 and extrapolate them, on the basis of assumptions about capital accumulation, labour force, productivity experience and convergence, out to 2025 (Kharas and Rogerson, 2012, p. 7).

Large differences are immediately evident: the Kharas and Rogerson (2012) estimate of $2 poverty for 2005 is 1.6bn compared to the World Bank's 2.6bn – in short there is a difference of a billion more people who are poor by the World Bank's method (survey mean) compared to the Kharas-Rogerson method (NA mean with unadjusted poverty line). Furthermore, the Kharas-Rogerson dataset predicts that poverty at $2 will be eradicated in India, Pakistan and Indonesia by 2015/6 which according to the World Bank are home to 1bn $2 poor in 2008.[5] Further, when Kharas and Rogerson say they are estimating $2

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2 The paper also considers combinations of economic growth and distributional changes to see what would allow the optimistic trajectory to be attained.

3 A fuller explanation of the rationale behind these scenarios can be found in Karver et al. (2012).

4 This approach is often referred to as the 'Sala-i-Martin' method since an early influential exposition of the use of NA means with survey distributions was provided by Sala-i-Martin (2002).

5 World Bank data for 2008 estimated from PovcalNet. World Bank (2011) does not give country level data for future estimates of poverty. Source for Kharas-Rogerson country level data is accompanying dataset on Brookings website at: www.brookings.edu/research/interactives/development-aid-governance-indicators.

poverty their poverty line is not comparable with the $2 poverty line applied by the World Bank. This is because the Kharas and Rogerson analysis uses NA means, rather than the survey means without adjusting the poverty line to allow for systematic bias between the two types of mean. This point can be illustrated by comparing the Kharas-Rogerson poverty headcounts with World Bank estimates back to 1995 (see Table 1). It appears that the $2 a day line used by Kharas and Rogerson lies currently somewhere between the World Bank's $1.25 a day and $2 a day poverty lines, and is probably rather closer to the $1.25 a day line.[6]

Table 1: Comparison of Kharas and World Bank estimates of global poverty headcounts (billions)

	Kharas (2010)	*World Bank*	*World Bank*
Poverty line (nominal)	$2 a day	$1.25 a day	$2 a day
1995	2.10	1.66 (1996)	2.80 (1996)
2005	1.58	1.38	2.56
2015	0.72	0.88	2.0

Source: World Bank data from Chen and Ravallion (2010); World Bank (2011).

The use of NA rather than survey means make it necessary to adjust the poverty line(s) to allow for the systematic differences between the two means as Hillebrand, (2008) for one notes. Hillebrand (2008) uses NA data and projections from the International Futures Model[7] to forecast global poverty in 2015 and 2050 and applies a poverty line of $1.50 in 1993 PPP $, which, following Bhalla (2002), he considers to be roughly equivalent to the World Bank's dollar-a-day poverty line (which was in fact $1.08 a day in 1993 PPP $) (Hillebrand, 2008, p. 729). In effect, indicating that when one calculates distributions using NA consumption means, rather than survey means, it is necessary to inflate the dollar-a-day poverty line by a factor of 1.4 to produce an 'equivalent' poverty line for use with NA means.

6 Further evidence of the need to recognise that poverty lines need to be adjusted when using NA means is provided in another paper by Kharas (2010) where he presents results derived from NA means which show that in India in 2005 there was no $1.25 poverty and that the $2.50 poverty rate was around 35%. In stark contrast (and probably more plausibly since it is hard to believe that extreme poverty had been eradicated in India in 2005) the World Bank estimated India's 2005 $1.25 poverty rate as 41.6% and the $2.50 poverty rate as 85.7% (see Chen and Ravallion, 2010).

7 Available at: www.du.edu/~bhughes/ifs.html

Hillebrand's method for developing a global distribution uses Bhalla's (2002) simple accounting procedure whereby the national income distribution (quintile and decile) data is first approximated by a continuous Lorenz function. This estimated function is then used to determine numbers of people and average income per capita for each percentile of the national population. The percentiles from all countries are then rank ordered by average income per capita before being aggregated to construct a global Lorenz curve. Two limitations of this method are, first, that the assumption that national income distributions can be reliably modelled by a continuous function risks degrading some of the input level detail of the survey data (quintile and decile totals in the model may not be identical to the actual input figures). Second, the assumption that all members of a given national percentile have the same mean income leads to some under-estimation of national inequality.[8]Based on the assumption that consumption grows in proportion to future estimates of GDP, Hillebrand estimates global poverty under both an optimistic (high-growth, 'high-globalisation' and 'world peace') scenario projection and a (perhaps more realistic) scenario in which national growth trends from 1981 to 2005 continue out to 2050.

Hillebrand also attempts to estimate the effect of differing assumptions concerning the impact of future growth on national income distributions. In addition to a static-distribution assumption, Hillebrand explores two different estimates of possible future changes in within-country distribution; one of which anticipates lessening inequality within countries while the other anticipates increasing inequality.[9] Hillebrand (2008) forecasts that under the high-growth scenario with static inequality, extreme poverty ($1 a day) will fall from 965 million in 2005 to 792 million in 2015 and to 353 million in 2050. Under conditions of lessening inequality the 2050 poverty headcount could be as low as 248 million, while under conditions of increasing inequality it could be as much as 468 million. Under the lower 'trend-growth' scenario (and static inequality), global poverty might fall to 869 million in 2015 but then rise above current levels to 1,237 million in 2050. These findings illustrate how poverty forecasts are particularly sensitive to variations in growth forecasts and to different assumptions about future inequality changes. We pick up this point in the later discussion.

8 The GrIP model (see below) avoids the first of these problems by using a method of linear interpolation that ensures that quintile, and upper and lower decile, data is precisely reproduced in the model. Regarding the second problem, national percentiles include widely differing numbers of people since, for example, within a single percentile for China or India we would find around 12 or 13 million people all assumed to have the same income per capita whereas for the UK a percentile would include only around 600,000 people. This is evidently a source of some distortion in the model, particularly when looking at poverty counts since many of the poorest countries are also the most highly populated. The GrIP model overcomes this problem by calculating how many people there are in each country who fall within a sequence of increasing income brackets and then summing across all countries the total number within each income bracket.

9 The 'lessening inequality' estimate is derived from Higgins and Williamson (2002) and the 'increasing inequality' estimate is derived from World Bank (2007).

One final study of note is that by Dercon and Lea (2012) which projects $2 poverty – and, interestingly other types of poverty such as child stunting, and maternal mortality – to 2030 based on different growth scenarios. This study combines poverty semi-elasticities (estimated from the PovcalNet dataset) and forecasts for survey means. The growth scenarios for the means seek to show max/min ranges for economic growth. The low-growth scenario is average growth for each country in the 1990s. The high-growth scenario is the average of 2000–2016 WEO actual and projected growth rates. The paper concludes that in 2030 most of the world's poor will live in middle-income countries (MICs), and that this will largely be accounted for by poverty in India and Nigeria.

Dercon and Lea's use of semi-elasticities is problematic though because as Lenagala and Ram (2010) show, semi-elasticities – the elasticity of poverty with respect to real GDP pc or the ratio of the fall in the poverty rate to the percentage increase in real GDP per capita – is not stable over time and is sensitive to different poverty lines even within the same country. Lenagala and Ram (2010) note that the elasticities generally decline over time – the poverty-reducing impact of income growth weakens over time. Further, there are 'huge differences' across different poverty lines with elasticities for $2 (and $2.50 poverty) being 'dramatically lower' than for $1/day. When one looks closely at national distributions there are good reasons why semi-elasticities vary like this – in essence the problem is that the semi-elasticity at a given poverty line bears little relation to the actual shape of the national income distribution curve at that same point. In short, the mathematical relationship assumed in the calculation of the semi-elasticity has little logical correspondence to what actually happens as income growth shifts the national distribution curve.

2.3. The use of National Accounts and Survey means

Comparisons between the use of NA and survey means on estimates of current and historic poverty are not new (see for example, Ravallion, 2003; Deaton, 2005). Most recently, Dhongde and Minoiu (2013) review and discuss in considerable detail the sensitivity of historical estimates of aggregate global poverty headcounts both to differences between survey and NA statistics and to differences in the statistical techniques used to model the distribution curves. They conclude that:

> estimates of global poverty vary significantly when they are based alternately on data from household surveys versus national accounts but are relatively consistent across estimation methods… [C]onceptually it is difficult to defend replacing the survey mean with the national accounts mean to anchor relative distributions from surveys (Dhongde and Minoiu, 2013, p. 1 and 11)

Dhongde and Minoiu (2013) recognise that there are systemic differences between the survey and NA means such that NA means are higher than survey means. However, they do not adjust the poverty line to allow for this bias (without this adjustment it would indeed be difficult to defend replacing survey means with NA means as they note). As we discuss above, since there are systemic differences between these means a proper comparison would require adjustment of the poverty lines when used with NA means. Since most forecasts of global poverty rely on one or other but rarely compare both types of means, Dhongde and Minoiu do helpfully identify that the choice of mean almost certainly accounts for much (although by no means all) of the difference between different analyses published in different papers. However, they overlook two significant issues. Firstly, since the World Bank poverty lines were originally applied to analyses based on survey data it is almost perverse that, when confronted with this systemic bias, most researchers – with a few notable exceptions such as Hillebrand (2008) – do not recognise the importance of adjusting the poverty line to take account of this bias. Without such adjustment it is hard to claim that even the most basic attempt has been made to develop analyses that can be compared to the work of others. Second, since there is not a simple, universal relationship between survey and NA means (the ratio of NA mean to survey mean shows great variability between countries) the decision whether to use survey or NA means has significant implications for not just the scale but also the location of global poverty. We discuss these issues in more detail later when we explain how the GrIP model enables us to take them into account. A key benefit of the GrIP model is that it readily enables us to make direct comparisons between different approaches to these issues in a single model that can be held constant in all other respects.

The choice of type of mean is significant because there are two distinct discrepancies between survey means and NA means. First, they generate different levels of consumption; and second, they generate different growth in consumption (which is the reason why for a given country the ratio of NA mean to survey mean – the NA/S ratio – changes over time). For example, India's consumption means are considerably lower from surveys than from NAs, and this difference widens over time as the growth rate from NAs is far greater than that indicated by the surveys. Ravallion (2012, p. 7, footnote 16) argues that '[f]or most countries, about 90% of the national accounts growth rate is passed onto the survey means, but for India it was only about half'.[10]

As we have seen above, estimates and forecasts of global poverty variously use survey or NA means, but none of the studies we describe above identify explicitly the different impacts of the selection of mean on the scale and location of poverty. Survey means are the average income or consumption per capita as measured in national surveys (i.e. in the same surveys that are used to derive the national income or consumption distributions) whereas NA means are derived from national macroeconomic data. We can therefore understand survey means as 'bottom-up' measures of average per capita income or consumption in a country and NA means as 'top-down' measures of income or consumption. In theory we would

10 We understand that the World Bank adjusts for this discrepancy in growth rates by systematically applying discounts to NA-derived growth projections for India. This type of adjustment is also applied to China's forecast survey means, although in this case it could be mainly as a proxy to allow for the continuation of rising inequality seen in China (and to a lesser extent in India) in recent decades. The focus on adjusting growth rates for just these two countries is presumably because they are systematically so important to the global count.

expect to see some strong correlation between these means but in practice reliable correlations are difficult to identify. For example, for current low-income countries (LICs) the average ratio of the NA Household Final Consumption (HFC) mean to consumption from survey means (the NA/S ratio for HFC) is 1.03. While this average figure may not be unreasonable, values for individual countries vary widely between 0.57 (Ethiopia in 1995) and 3.66 (Madagascar in 1980).[11] Applying the NA mean, rather than the survey mean, to the survey distribution for Ethiopia would therefore significantly reduce the modelled consumption of the population, and hence increase the estimated poverty headcount. In Madagascar on the other hand, use of the NA mean would lead to much lower poverty levels relative to those derived from the survey mean.

In the debate over whether it is better to rely on survey or NA means when estimating sub-national and trans-national[12] income or consumption levels there are arguments for and against each position. There is, however, no compelling reason why we should 'trust' one set of data more than the other. Differences in concepts, measurement errors (in both NA and survey methods), sampling problems and the fact that some NA measures, notably household consumption (HFC), are not measured directly but are estimated as residuals from other measurements, all mean that '[i]t should not be assumed that national accounts data are more accurate than survey data for developing countries.' (Ravallion, 2012).[13]

On the one hand, it makes sense to use the survey means since they are derived from the same surveys as the distributions. After all, if one chose to trust the survey distributions why would we not also trust the survey means? On the other hand, if NA data shows that the survey means significantly underestimate the national average per capita consumption (which is the case since average NA/S ratios for HFC are around 1.6, implying that survey means only identify about 60% of total household consumption) then should we not include the 'missing millions' of consumption somehow, particularly when, as here, we are making between-country comparisons?

One way to make sense of the relevance or impact of the different approaches (survey or NA mean) is that, when considering any poverty line, if one uses data derived from the survey mean (as is the case with PovcalNet derived estimates of poverty) then the implicit assumption is that any 'missing millions' between the survey and NA mean are distributed among, or accrue to, only those peoples above the poverty line. In other words, you accept the accuracy and validity of the survey distribution below the poverty line but reject its

11 For middle-income countries (MICs), the average NA/S ratio is 1.57 but also varies widely between a minimum of 0.57 (Lesotho in 1994) and a maximum of 4.50 (Swaziland in 2009).

12 The term 'trans-national' is used here to refer to analyses where aggregations and comparisons are made which include both international, or 'between-country', differences (differences arising from differences between national per capita means) and sub-national, or 'within-country', differences (differences arising from national distributions of income or consumption).

13 For a fuller description of the issues see also Dhongde and Minoiu (2013).

validity above the poverty line. Alternatively, if you apply the NA mean to the survey distribution then you assume that the missing millions are distributed across a country's entire population in proportion to the surveyed distribution. In other words, you accept the validity of the survey distribution but reject the validity of the survey mean. It transpires therefore that once the survey versus NA discrepancy is recognised it becomes difficult to argue that combining survey distributions with survey means is necessarily better than combining the distributions with NA means. Either approach requires an implicit 'calling into question' of some part of the 'bottom-up' national survey.

In theory there might be a way to use survey means and distributions below the poverty line while 'spreading' the missing millions across the higher income population. However, in practice this would be a rather speculative exercise. In part this is because the lack of clear correlation between NA mean, survey mean and distribution inequality would make estimate of a modified distribution very difficult. But also it is because any such spreading would be dependent on the threshold above which the missing millions would be distributed. Different thresholds would lead to different estimates of actually existing national income or consumption distributions.

In view of all these limitations a case can be made that if we want to explore the full range of possible poverty scenarios then we should not only rely on survey means but should also make forecasts derived using NA means with survey distributions. However, when doing this it is important to recall that this method of analysis allocates some of the missing millions to people living below the poverty line. Therefore, notwithstanding that the data used in the model may all be consistently in constant PPP US dollars, we may need to adjust the poverty line used for comparisons. In other words, the 'dollar-a-day' poverty lines applied to PovcalNet-type analyses may need to be increased in order to determine a broadly comparable poverty line to apply when NA means are used in the analysis. It is important to note here that this point – that the poverty line *needs* adjustment when NA means are used – has not been widely practiced to date.

3. A new model to compare method and assumptions

3.1. The GrIP model

We introduce here the GrIP model, which has been developed from an earlier model described in Edward (2006). The main objective of the GrIP model is to construct a truly global model of consumption distribution that allows ready comparison of different assumptions (such as the use of survey means or NA means) while avoiding some of the pitfalls of other models.

The GrIP model enables the combination of survey distributions with either survey means or NA means. Survey distributions (quintile and upper and lower decile data) are taken (in the following order of preference) from PovcalNet, World Development Indicators or the

UNU WIID V2.0c (May 2008) database.[14] Survey means are taken from PovcalNet and NA means are taken from World Development Indicators (all analysis and results are in 2005 PPP $). This approach enables the model to cover more countries than just those in PovcalNet.[15]

Even though these datasets have greatly improved their global coverage in recent years, there are still some significant gaps in the data so that in order to construct a truly global distribution it remains necessary to estimate some missing data. Surveys do not take place annually so in the GrIP model when making historical estimates distributions for intermediate years between surveys are calculated by interpolation.

This still leaves situations where a country has no surveys or the gaps between surveys are considered to be too great to allow reliable interpolation. In these cases the GrIP model allows the choice on how to 'fill' a country's missing distributions with the (non population-weighted) average distribution from all other countries in the same region and income group (i.e. the analysis can either be 'filled' to include these estimates or 'not filled' which means that the analysis only includes countries for which national distribution data is available). Such an approach is used by Chen and Ravallion (2010; 2012) but only based on regional averages, not on income categories (although since PovcalNet only covers developing countries this limitation may be less significant in their work than it would be if extended to GrIP's truly global coverage).

Unlike approaches which use elasticities or semi-elasticities (e.g. Dercon and Lea, 2012), or reduce the specificity of the raw quintile/decile distribution data to an idealised continuous function (Kharas, 2010), the GrIP model uses a linear interpolation method (described in more detail in Edward, 2006) that ensures that sub-quintile dis-aggregations of the distribution still accurately retain the exact quintile (and upper and lower decile) survey values that are input to the model. Furthermore, by disaggregating the national populations into globally standard US$ per capita brackets, the GrIP model avoids introducing the distortions of approaches, such as Bhalla's simple accounting procedure (Bhalla, 2002; Hillebrand, 2008), where by disaggregating only to percentiles some large step-change distortions are introduced in the later global aggregation, at points where percentiles from the very largest countries (such as India and China where each percentile currently includes well over 10 million people) are added back into the global distribution.

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14 See www.wider.unu.edu/research/Database/en_GB/database. Where WIID V2.0c is used consumption distributions are used in preference to income distributions. No attempts are made to modify income distributions to 'convert' them to consumption distributions. Such attempts at conversions are too speculative to be justified.

15 This feature, which is predominantly introduced so that the model can be used to look at the entire global consumption (or income) distribution and not just at the lowest income regions, is particularly useful when investigating issues such as the emergence of a global middle-class and identifying winners and losers in the globalisation process.

As noted above, the GrIP model allows for the use of *survey means* (Option 1 in the model) or *NA means* (Option 2 in the model). When using survey means (Option 1), for countries where there is distribution data but no survey mean, an estimated mean is calculated from NA data based on global relationships between NA and survey means (the 'NA/S ratio') for other countries in the same income category. When using NA means (Option 2) the NA mean is applied directly to the survey distribution.

Various NA measures are candidates as the source of the NA means: GDP per capita or Household Final Consumption (HFC) per capita being the most useful. In this paper all the figures are based on HFC means (in 2005 PPP $).[16] Because coverage of GDP data is generally better than that of HFC data, where GDP data exists but HFC data does not then the missing HFC figure is estimated from the GDP data. Wherever possible this is done in a given year by applying the most recent HFC/GDP ratio for the country in question. Where no such ratio exists then the average ratio calculated for all countries with suitable data in the same region and income category is used.

Table 2: Coverage of analysis and effects of estimating HFC and filling distributions

	Source data coverage			After estimating missing HFC			After filling missing distributions		
Year	No. of countries	Pop'n cov. (%)	Consum-ption cov. (%)	No. of countries	Pop'n cov. (%)	Consum-ption cov. (%)	No. of countr ies	Pop'n cov. (%)	Consum-ption cov. (%)
1980	62	71.7	72.6	79	81.2	83.9	132	85.9	87.7
1990	97	84.4	81.0	131	94.0	92.6	167	96.3	94.3
2000	118	87.2	82.7	156	96.2	91.2	181	97.4	92.5
2010	102	83.4	78.4	135	91.9	80.1	178	96.6	89.6

Source: GrIP v1.0. Note: This table is not affected by Option 1 or 2 selection. Percentages are of global totals.

Table 2 illustrates how by first estimating missing HFC data from GDP data (for countries that otherwise have valid survey distributions) and then using filling to estimate distributions for countries without valid surveys, the GrIP model incrementally builds a global model from the available source data. It can be clearly seen that the number of countries underpinning the model, and hence also the reliability of any outputs from the model, reduces rapidly once we go back into the 1980s. For this reason the results given here do not generally go back further than 1990.

In order to produce growth scenarios we use somewhat similar assumptions to those in Karver et al. (2012) but derive the forecast rates from more recent IMF WEO figures. This means the estimates are based on the average growth rate from 2010–2017 (rather than

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16 GrIP has been built to allow ready comparison of different types of NA mean but to avoid over-complication here we use only HFC throughout this paper.

2009–2016 used by Karver et al.). We therefore use the following three scenarios for GDP PPP growth estimates as the forecast growth rate for 2010–2040:[17]

- Optimistic: uses WEO GDP PPP average growth 2010–2017;
- Moderate: uses WEO GDP PPP average growth 2010–2017 minus 1%;
- Pessimistic: uses 50% of WEO GDP PPP average growth 2010–2017.

In our forecasts, some other adjustments were also made to remove some anomalies which we list in this footnote for transparency.[18] The resulting national growth rates in each scenario are then applied to the GDP PPP values for 2010 taken from the World Bank WDI. This ensures consistency with the rest of the GrIP model which uses WDI rather than IMF GDP data.[19]

17 When selecting these scenarios we also considered similar scenarios used by others: (a) Assume the IMF's furthest out WEO forecast rate (2016–17 in our case) is the best estimate of medium-term growth rate and apply this to all years post-2017; (b) use WEO forecasts to 2017 but beyond those cut long-term growth rates in half (i.e. to 50% of the 2016–2017 rate); (c) subtract 1% from growth forecast for all years from current year; (d) use historical averages from last 15 years (1995 to 2010) as growth forecast for next 15 years (Dercon and Lea, 2012, also make a similar estimate). While we have not made direct comparisons of our scenarios with those other forecasts we have rejected them on the following basis: (a) and (b) both rely on forecasts for single years being sustained subsequently over the next two decades. Where those forecasts yield growth rates higher than our optimistic model then we would be concerned that they could not be sustained over such a long period. Where the forecasts show lower growth rates then our optimistic model would over-estimate growth and hence provide an 'upper-bound' estimate – which is what we consider an optimistic model should be aiming to provide. It is not self-evidently clear that our pessimistic forecast yields a lower global growth rate (i.e. provides a more pessimistic 'lower-bound') than Moss and Leo's (2011) option (b). However, given that our scenario halves growth from 2010, rather than 2017 in (b), and then also subtracts 1% from that growth, we would expect our pessimistic scenario to be a lower-growth scenario than either (b) or (b) plus (c). With reference to (d), while historical averages may be interesting we are inclined to presume that these have already been taken into account in forming the IMF's WEO forecasts. We do not therefore think that there is any reason to suppose that forecasts based on the historical averages are any more justifiable than those derived, as ours are, from the WEO forecasts.

18 These are as follows: where the moderate rate estimate is lower than the pessimistic (as when the WEO growth estimate is negative, e.g. Greece) then the moderate value is used. In one case, Syria, WEO has no estimate so a growth rate of zero is assumed. We calculate the GDP PPP growth rates for our scenarios by converting each country's WEO figures for GDP PPP in current international $ in 2010 and 2017 into 2005 international $, using the relevant WEO GDP deflator forecasts for the USA. 2010–2017 GDP PPP growth rates for each country are then calculated from these constant 2005 international $ figures. Population forecasts are taken from the UN population division medium variant population forecasts from United Nations, Department of Economic and Social Affairs, Population Division (2011). World Population Prospects: The 2010 Revision, CD-ROM Edition.

19 IMF's WEO and World Bank WDI figures for GDP PPP at current international $ largely agree. With the exception of Russia and Mexico, the two datasets agree within 10% for the 14 economies over $1tn GDP PPP each and which collectively accounted for 70% of global GDP PPP in 2010. Nevertheless, some differences do exist so this approach maximises consistency and comparability between historical analysis and forecasts within GrIP. IMF WEO figures were taken from the April 2012 update. WDI figures were from the Feb 2012 update.

We explore the impact that a dynamic inequality estimate might have on the results, deriving our estimates of future within-country distributions from extrapolation of historical data. To do this we extrapolate the distribution change in the model from 1989 to 2009 out into the future (linear extrapolation applied to distributions, urban-rural ratio and NA/S ratios).[20] The main purpose of this dynamic analysis is to investigate whether the assumption of static distribution, as used by others, introduces a significant difference in the calculations. Because the dynamic inequality assumption introduces even more uncertainty into the forecasts we prefer only to extend those forecasts out to 2030.

Recognising that within-country inequality can decrease, we also explore the significance of the impact of this by providing forecasts calculated using a 'best' (i.e. most equal) historical distribution for each country. The 'best distribution' for a given country was taken as the survey distribution that had the lowest ratio of the highest quintile to the lowest quintile (Q5/Q1).[21]

In sum, we use three inequality scenarios to illustrate the impact of different inequality assumptions as follows:

a) 'static inequality' = growth scenarios with static inequality;

b) 'dynamic inequality' = growth scenarios with dynamic changes in distribution, urban-rural ratio (China, India and Indonesia only), and NA/S ratios. Future changes are estimated by linear extrapolation of the trends calculated for each country from 1989 to 2009; and

c) 'best ever distribution' = moderate growth scenario with the lowest-inequality historical distribution (in the PovcalNet dataset) for each country.

A limitation of the dynamic, or 'extrapolated', forecast is that it is dependent on the availability of data. Since many of the poorest countries are those with the most limited data (e.g. DRC has only one survey and therefore we cannot predict distribution changes for DRC so have to treat it as static) this dynamic forecast may well significantly mis-state the effect of distribution changes, but it does give a 'feel' for the implications of the static distribution assumption.

We have already noted some of the problems that can arise when trying to make comparisons between model results based on survey means (Option 1) and those based on NA means (Option 2). As a minimum, when using NA means in a model some attempt

20 Rural/urban applies to China, India and Indonesia only.

21 This adjustment was applied only to countries with distribution data in PovcalNet. We consider that since the 'best distribution' is already rather speculative it would be unwise to further complicate the analysis by introducing survey data from multiple sources here, preferring instead to rely only on the subset of high quality data that is provided by PovcalNet.

needs to be made to adjust the survey-mean derived poverty lines to take account of the systematic difference between survey and NA means (and even then a direct comparison is not possible because, as discussed earlier, differences in the relative values of the means have the effect of changing the weighting that each country has in the global distribution and hence also changing the apparent geography of global poverty).

In this paper we adjust the poverty line applied to Option 2 (NA) to give the same global poverty headcount in 2005 as that calculated for each of the three unadjusted poverty lines ($1.25, $2 or $10 a day) when applied to Option 1 (S). The adjusted poverty lines used in Option 2 are $1.75, $2.9 and $15.4 (2005 $ PPP) although for ease of comprehension we still refer to these as the $1.25, $2 and $10 poverty lines since those are the Option 1 values to which these Option 2 lines are (broadly) equivalent. The multipliers applied to each of these poverty lines are therefore 1.40, 1.45 and 1.54 respectively. It is noteworthy that the 1.40 multiplier for the $1.25 line is the same as that proposed by Bhalla (2002) and adopted by Hillebrand (2008) even though our multiplier is derived entirely independently of their work.

In sum, the GrIP model provides three improvements over other models. First, the GrIP model has been built to allow the estimation of national distributions using *either* survey means (as used by the World Bank in PovcalNet) *or* National Account (NA) means. The selection of means is a fundamental difference between the two commonly used approaches to poverty modelling and it is one that has significant influence on both the scale and the location of poverty estimated in the model. The GrIP model therefore enables direct comparisons to be made between these two key approaches in a model that holds all other assumptions constant. Second, unlike models such as the World Bank's PovcalNet (Feb 2012) which covers only 130 countries, the GrIP model does provide a more global model of inequality and poverty by covering 178 countries representing 97% of the global population.[22] And third, a central feature of the GrIP model is that (at the expense of incurring significant computational complexity) it has been developed carefully to ensure that the detail of input data is faithfully replicated in the model. By contrast, in various other current models of global income distribution simplifying assumptions are made either by ignoring some elements of the sub-national distribution profile (e.g. Milanovic, 2012) or by 'fitting' the national profile to an idealised mathematical functional form (e.g. Chotikapanich et al., 2007; Pinkovskiy and Sala-i-Martin, 2009). Unlike the GrIP model, these sorts of

22 Figures refer to 2010. Figures vary slightly for other years due to availability of data. The validation of the GrIP historical data against World Bank data is presented in Edward and Sumner (2013). The April 2013 Povcal Update and analysis (see World Bank, 2013) shows some minor differences to GrIP. The main difference is that the GrIP survey result presented here of 1.1 bn for 2010 extreme ($1.25) poor using survey means compares to a World Bank (2013) estimate of 1.2bn. This is because the GrIP estimates in this paper are based on the 'filled' list of countries which, as is shown here, includes slightly less than 100% of the global population. To compare GrIP to World Bank totals we need to make an adjustment (coverage compensation) for missing countries. If we were to adjust the 2010 headcounts in this paper by making this coverage compensation we would get close to the World Bank's 1.2bn figure in 2010 (in 2008 for instance coverage compensation would add 100 million to the global $1.25 poor headcount).

approaches can involve degrading the source (quintile and decile) data on distributions so that the reproductions of the national distributions in the model become inherently different to those indicated by the data input to the model.

4. Estimating global poverty in the future

We next take the GrIP v1.0 model and make global poverty projections to show how much difference method and assumptions make. We present separate forecasts derived using survey means (Option 1), which provide optimum comparability to World Bank figures, and NA means (Option 2, using HFC means). In the forecasts we also reflect the changing levels of national prosperity by re-classifying the countries into their forecast country income category (LIC, MIC and other categories). We do this using forecast GNI figures (derived by applying GDP multipliers from IMF WEO for the relevant forecast scenario calculated as described earlier). These GNI figures are then converted into GNI per capita figures in constant dollars and compared to inflated values of recent World Bank thresholds for determining country income category. Thresholds are inflated at the appropriate rate for the relevant forecast.[23]

Results of the analysis are shown in Figures 1 and 2 for $1.25 and $2 poverty with survey means. Figures 3 and 4 give results derived from NA means.

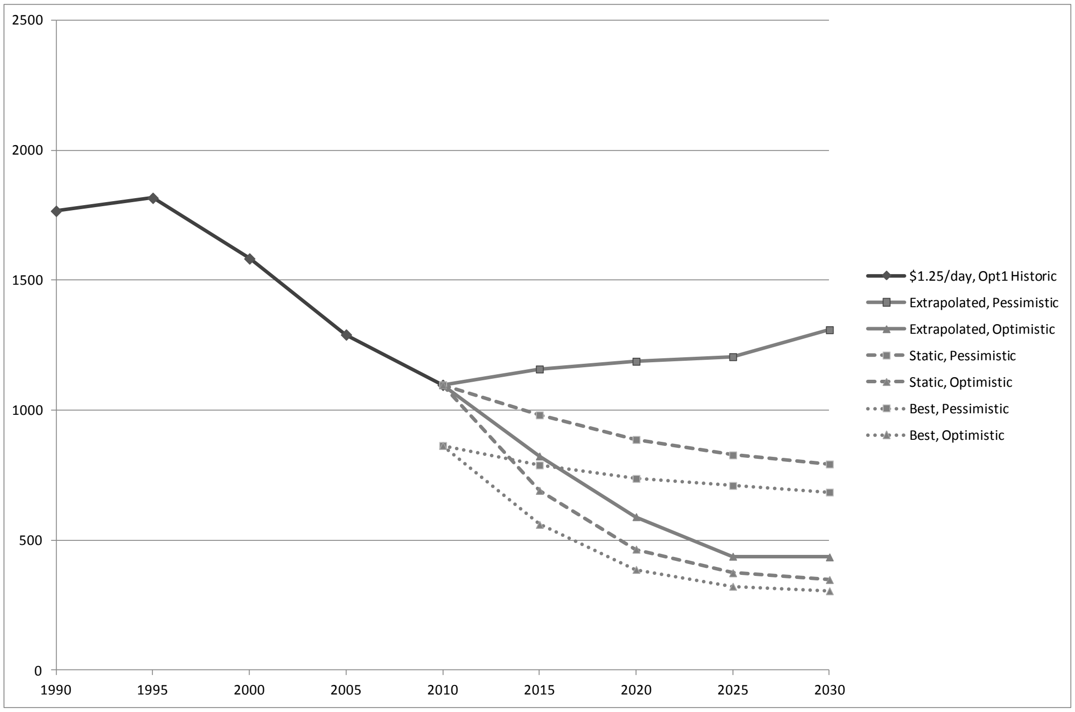
As has been documented in other studies (e.g. Karver et al., 2012; Ravallion, 2013), extreme poverty ($1.25) could conceivably, in the best-case situation (and using survey mean estimates), fall from current levels of just over 1bn to levels close to 300m (3–4% of world population) by 2030. However, this would require economic growth at 'optimistic' levels and changes in inequality towards each country's historic 'best ever' distribution.

Inequality changes become more significant under conditions of lower growth. For example, in the pessimistic scenario extreme poverty might fall from just over 1bn to 700m in 2030 assuming changes towards the 'best ever' distribution. However, if distributions remain static this fall would reduce by almost 150m, and if current inequality trends were to continue extreme poverty could actually increase to 1.3bn.

These figures are all for survey means. Use of NA means produces similar figures but with a lower range of differences. For example the best-case minimum poverty level is just over 400m in 2030 while the worst-case figure is 1.1bn.

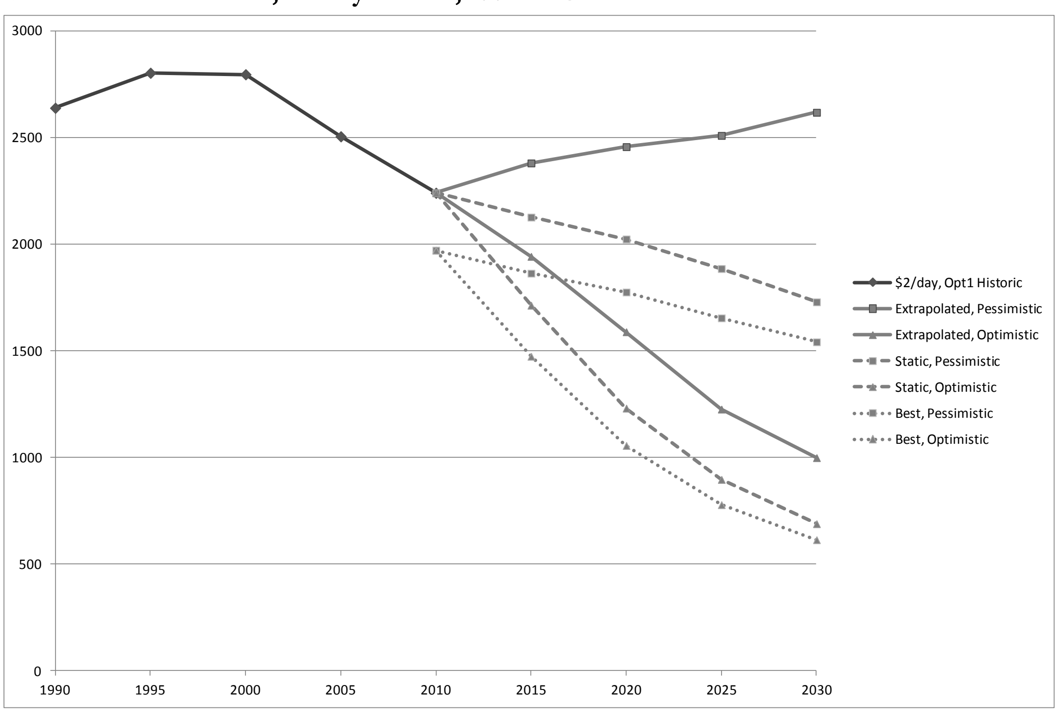
23 Country income categorisations, in GNI $ pc pa (2010 constant $) are: low-income (LIC) <= $1,005; lower middle-income (LMIC) $1,006–$3,975; upper middle-income (UMIC) $3,976–$12,275; high-income (HIC) > $12,275. These compare to current thresholds as follows: $1,025 or less; lower middle-income, $1,026–$4,035; upper middle-income, $4,036–$12,475; and high-income, $12,476 or more.

Figure 1: $1.25 headcount (millions), by pessimistic/optimistic growth and three distribution scenarios, survey means, 1990–2030



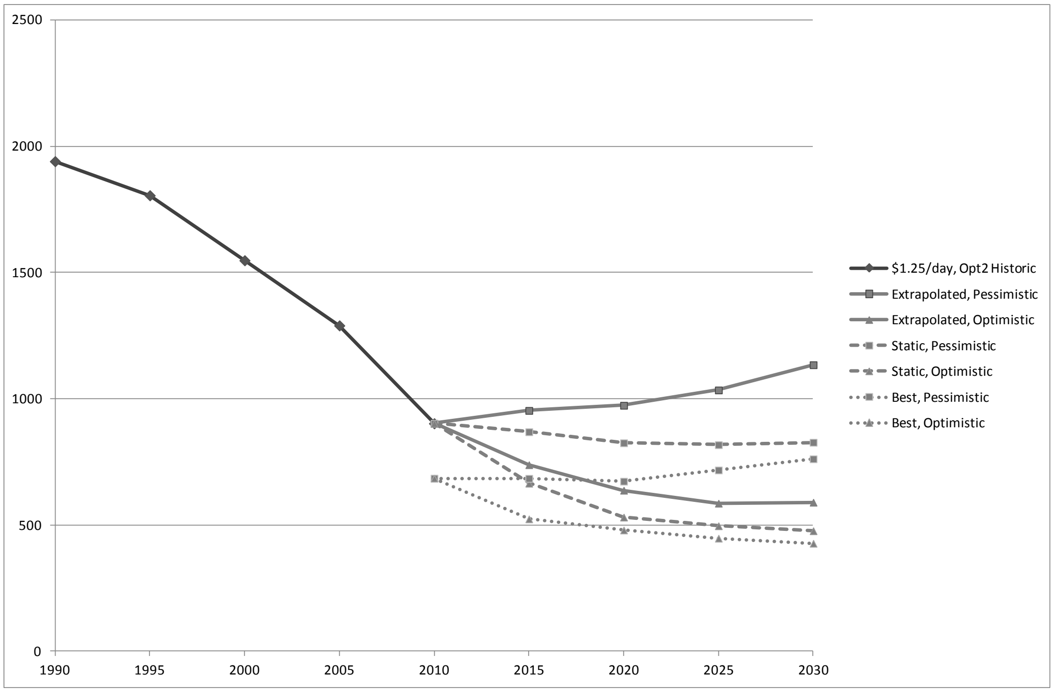
Source: Authors' own.

Figure 2: $2 headcount (millions), by pessimistic/optimistic growth and three distribution scenarios, survey means, 1990–2030



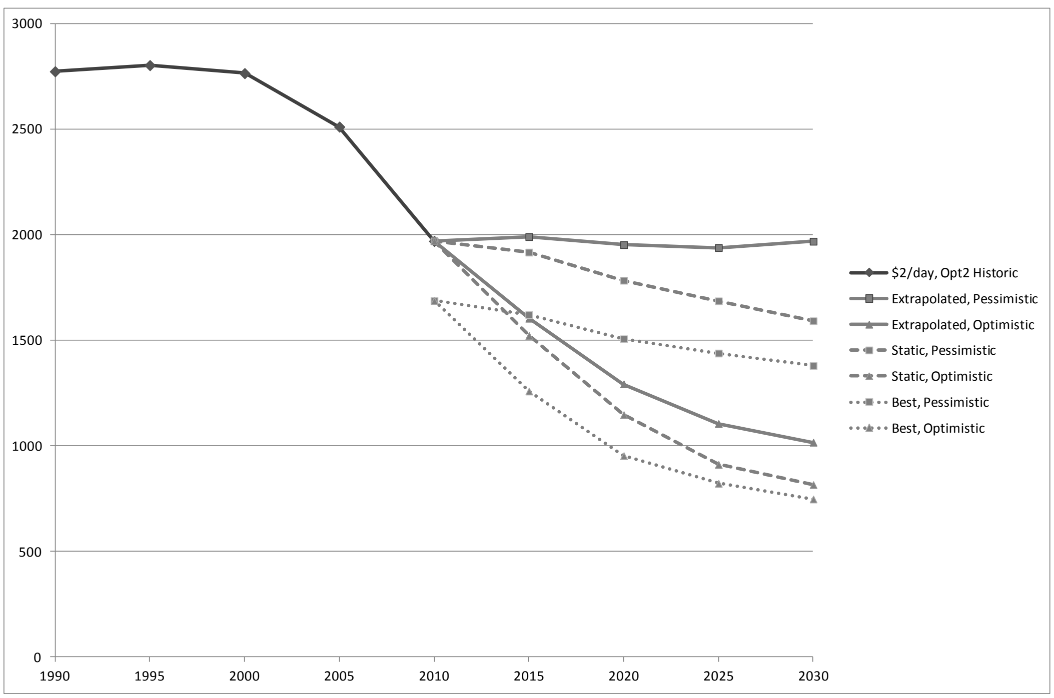
Source: Authors' own.

Figure 3: $1.25 headcount (millions), by pessimistic/optimistic growth and three distribution scenarios, NA means, 1990–2030



Source: Authors' own.

Figure 4: $2 headcount (millions), by pessimistic/optimistic growth and three distribution scenarios, NA means, 1990–2030



Source: Authors' own.

'Moderate' poverty ($2, the median poverty line for developing countries) will – not surprisingly – continue longer. However, even $2 poverty could fall from current levels of just over 2bn to 600m by 2030 – with 'optimistic' growth and if every country returned to its 'best ever' inequality. However, $2 poverty could also increase from current levels to exceed 2.5bn in 2030 if growth is weak and current inequality trends continue. (All figures for survey means. Again, NA means generate slightly smaller reductions and increases in poverty). It is startling just how much difference changes in inequality could make to global poverty in 2025 and beyond – to both the numbers of poor people and the costs of ending poverty. The difference between poverty estimated on current inequality trends versus a hypothetical return to 'best ever' inequality for every country could be an extra 400m $2 poor in 2030 even if there is optimistic growth. If growth is closer to the pessimistic scenario then these differences in inequality distributions could add an extra 1 billion people under the $2/day poverty line in 2030.

It is worth noting that there is a particularly large degree of uncertainty over current poverty levels and forecasts for India, and to a lesser degree in China. These two countries currently account for almost half of global $2 poverty and for a very high proportion of uncertainty in the poverty forecasts. Therefore effects in these two countries are likely to dominate any aggregation that they are included in.

Using the $2 line India accounts for 38% of global poverty in 2010 when survey means are used but just 21% when NA means are used. At the $1.25 line India accounts for about a third of global poverty using survey means but just one tenth of global poverty using NA means. In contrast, China's share of global poverty changes from one tenth (survey means) to one-fifth (NA means) while sub-Saharan Africa's share rises from less than one-third (survey means) to a half (NA means) of global $1.25 poverty (See Table 3).

Table 3: Proportion of global poverty by Region in 2010

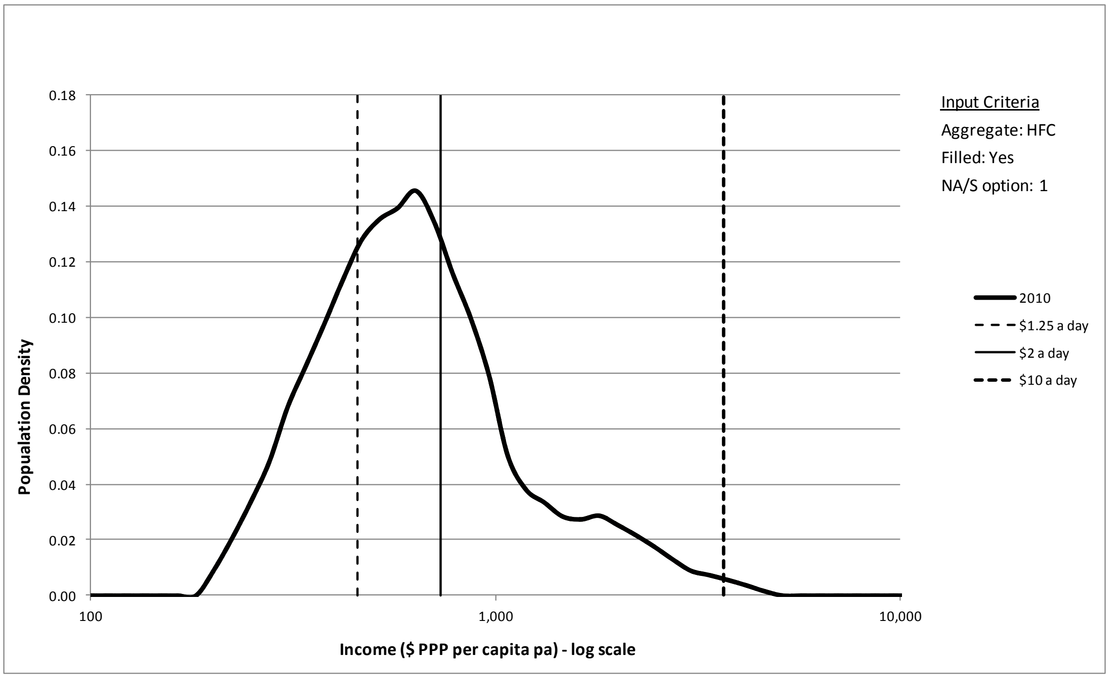
(S = survey mean; NA = national accounts mean)

	$1.25		**$2**	
Region	**S**	**NA**	**S**	**NA**
East Asia and Pacific	18%	26%	22%	31%
Europe & Ctrl Asia	1%	1%	1%	1%
LatAm & Caribbean	3%	4%	3%	4%
M East and N Africa	1%	2%	2%	2%
North America	0%	0%	0%	0%
South Asia Region	46%	18%	49%	32%
sub-Saharan Africa	31%	49%	23%	30%
China	11%	22%	14%	24%
India	36%	9%	38%	21%
World	100%	100%	100%	100%

Source: Authors' own.

The poverty headcount in India is particularly sensitive not only to this effect (sensitivity to use of different means) but also to the different growth rates. This is because a lot of the Indian population lies in the region of $1.25 to $2 a day (Figure 5) so that even relatively modest differences in the 'effective' poverty line applied can make major differences to the number of poor.

Figure 5: Population distribution curve for India



Source: Authors' own.

A closely related effect was referred to by Deaton (2010, p. 32) as the 'Indianization of poverty' that resulted when the $1 international poverty line becomes $1.25 (in Chen and Ravallion, 2008) on the basis that 200 million Indians lived then on between $1 and $1.25 pc:

> Because there are nearly 200 million Indians who live on between $1.00 and $1.25 a day, the increase in the line adds many more Indians to the counts than it adds Africans.

In considering the possible future location of poverty, because India and China account for such large proportions of global poverty in Figures 6 to 9 below results for India and China are plotted separately and are not included in any of the aggregations. This allows us to illustrate more clearly underlying trends across other countries and is consistent with the notion that India and China are so large and unique that they should be treated as special cases in any analysis of global poverty.

In considering the forecasts, the use of NA means significantly alters the location of poverty with the greatest influence arising from very different estimates for poverty in India. Even when using just surveys (which are probably more reliable than the NA numbers in this case) there is still a very wide range of possible poverty outcomes for India in 2030, ranging from total eradication of $2 poverty if growth is optimistic and inequality is static or returns to 'best ever', to 850m if growth is pessimistic and current inequality trends continue. Therefore the inherent uncertainties over growth and inequality, interacting with the fact that a large proportion of the Indian population live in the region of the $2 poverty line, means that in 2030 Indian $2 poverty could range anywhere between zero and 850m if one just bases calculations on survey means. This range encompasses the range of possible poverty headcounts from NA mean calculations.

In the following figures we plot for the $2 poverty line the maximum and minimum value across all 12 'growth and inequality' scenarios as well as the average (simple arithmetic mean) for the 12 scenarios. Figure 6 shows that in 2010 global poverty at $2 is largely focused in India and elsewhere in South Asia. This is particularly the case when using survey means, where South Asia (including India) alone accounts for 50% of global poverty while East Asia and sub-Saharan Africa account for 22% each and the rest of the world just over 5%. By contrast, with NA means, just under 95% of global poverty in 2010 is shared almost equally between South Asia, East Asia and sub-Saharan Africa.

In 2030 poverty in sub-Saharan Africa is expected to increase in almost all scenarios. If growth is pessimistic then this could increase poverty in the sub-Saharan Africa region by 250 to 350 million. Elsewhere in the world poverty will most probably decrease.[24]

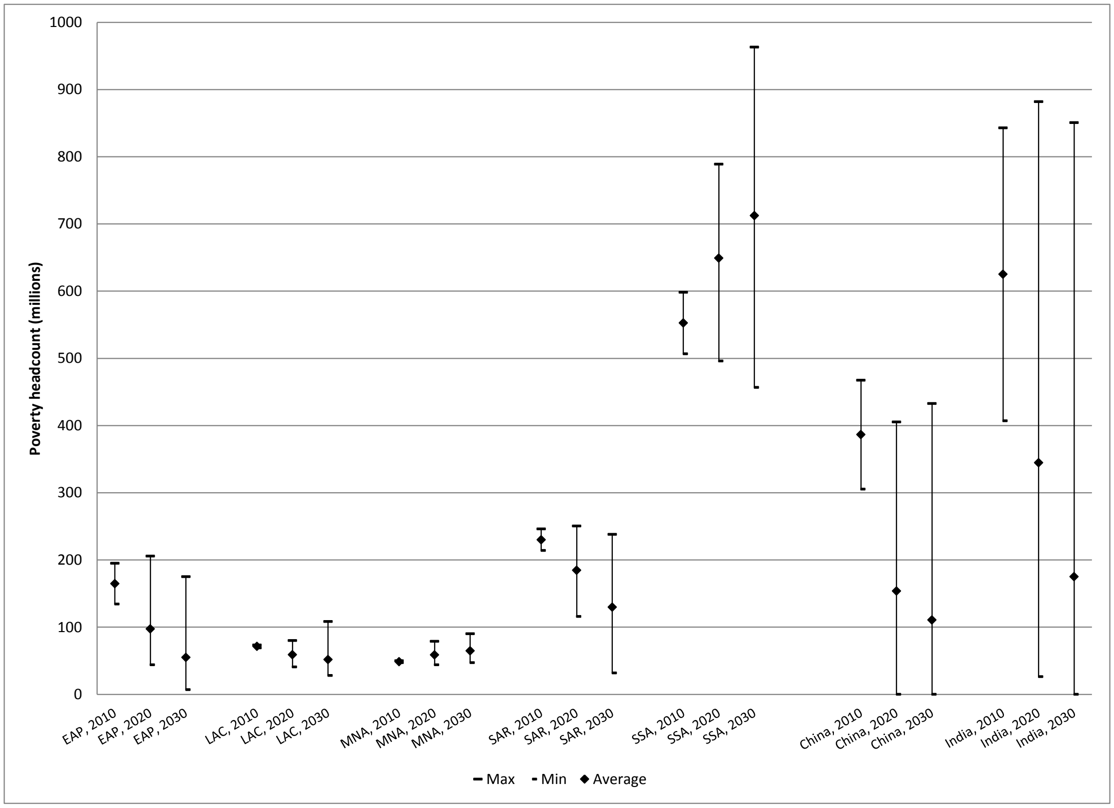
In India, where the greatest uncertainty exists, even if we discount the NA mean results as being unreasonably optimistic due to the large and widening discrepancies between NA and survey means there, it is still possible to envisage the eradication of $2 poverty in 2030 – as long as growth is optimistic and inequality remains static. But if growth is pessimistic (and inequality remains static) then in 2030 Indian $2 poverty would still be around 450m. If that was combined with current trends in increasing inequality then $2 poverty in India would remain at current levels (perhaps an unlikely scenario since it is plausible that it is the rapid growth in India in recent years that has driven its widening inequality).

In China the picture is slightly different with the possibility of almost eradicating $2 poverty under even the pessimistic scenario as long as inequality remains static. However, if current inequality trends continue then even with optimistic growth China may still have 150m to 200m $2 poor in 2030 (about 50% of current levels), and poverty may not even fall at all under the pessimistic scenario. It may seem from these figures, that poverty eradication in

24 Even with optimistic growth the SSA poverty headcount does not fall much due to some countries where economic growth rates are not expected to exceed population growth rates. Of course with pessimistic growth the numbers, and the list of countries showing rises, would be much more.

India is more dependent on economic growth while in China it is more dependent on curbing rising inequality. However, care needs to be taken as it may be that the rising divergence between NA and survey means in India is an indication of *de facto* rising inequality that is not visible in the surveys.

Figure 6: Distribution of global poverty, $2 poverty line, to 2030 by regions, by survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios



Source: Authors' own.

Note: EAP = East Asia and Pacific; LAC = Latin America and the Caribbean; MNA = the Middle East and North Africa; SAR = South Asia Region; SSA = sub-Saharan Africa. As described in the text, aggregations do not include China and India.

In the rest of Asia poverty seems likely to decrease with the size of the reduction being dependent mainly on the rate of economic growth. For example, in South Asia (excluding India) pessimistic growth produces reductions in poverty headcounts of less than 50m whereas optimistic growth might reduce current poverty levels (which are around 200m in 2010) by about 150m. Finally, while poverty in Latin America and in the Middle East and North Africa will remain relatively low it is likely to prove rather resistant to eradication, probably even rising slightly in the Middle East.

Figure 7 below shows that in 2010, global poverty at $2 is largely focused in MICs. China, India and all other MICs account for 78% (S) or 70% (NA) of $2 poverty.[25] By 2030 LIC poverty will probably have risen while MIC poverty is likely to have fallen (both in India and China and in other MICs). Recategorisation, as some countries graduate to MIC status, will also reduce the difference so that in 2030 poverty – outside China and India – may well be divided roughly equally between MICs and LICs. Across the forecast MIC/LIC split (excluding China and India and using forecast income categories) in 2030 using survey means there is, in all cases, more poverty in MICs (even after excluding China and India) than in LICs with the greatest difference being in the pessimistic-extrapolated scenario where MICs account for 29% of global poverty and LICs for 23% (with the remainder being in India and China). Using NA means neither category dominates the other in all cases and the greatest division is 48% in forecast LICs and 38% in MICs (but still 50% if China and India are included). It therefore seems that even after removing India and China, which are both already MICs, there is no strongly compelling case here for ignoring MIC poverty and focusing only on LIC poverty.

Kharas and Rogerson (2012, p. 5) argue that $2 poverty in 2025 will be focused in 'selected low-income and fragile countries'. Despite using two different lists of fragile states (the OECD list as used by Kharas and Rogerson and an alternative – the World Bank list of 'Fragile Situations')[26] we are unable to place the majority of world poverty in low-income

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25 Use of NA means raises the proportion of global poverty in LICs and UMICs (notably China) whilst reducing the proportion in LMICs – principally this is because NA means reduce the poverty in India from 38% (S) to 21% (NA) of global poverty.

26 See for lists World Bank (2013) and OECD (2013a). Arguably the World Bank list has stronger analytical basis because:

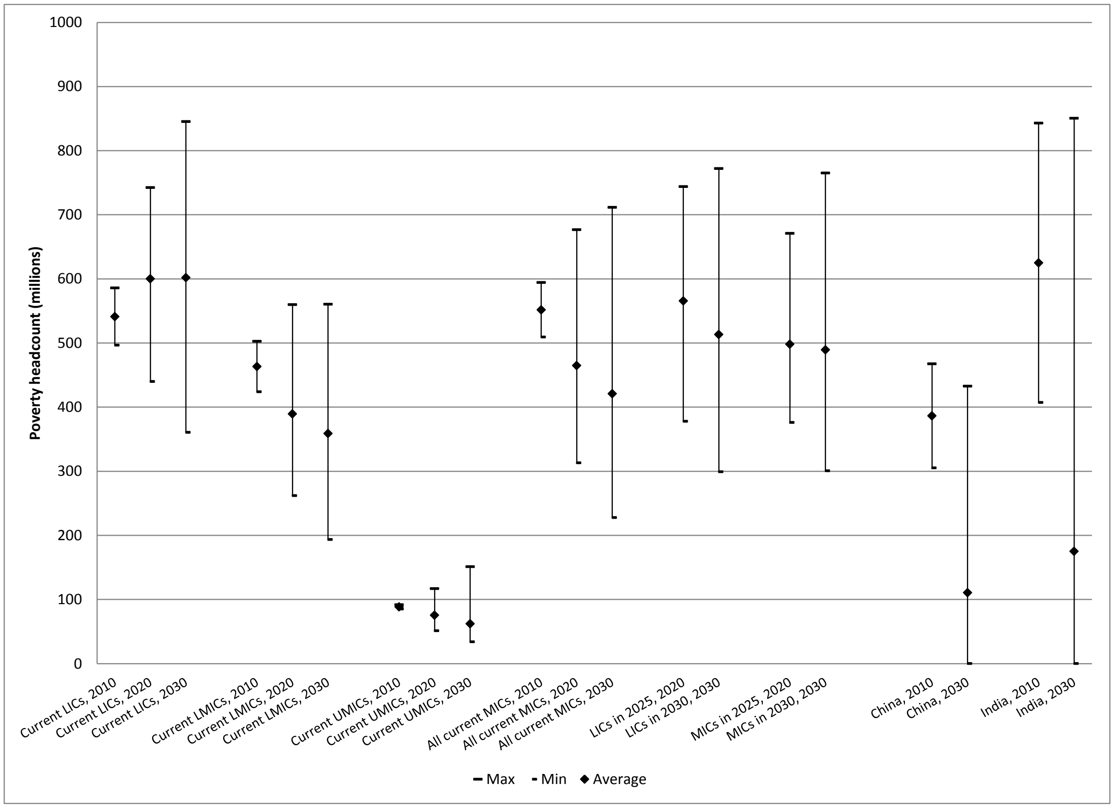
"Fragile Situations" have: either a) a harmonized average CPIA [Country Policy and Institutional Assessment] country rating of 3.2 or less, or b) the presence of a UN and/or regional peace-keeping or peace-building mission during the past three years. This list includes only IDA eligible countries and non-member or inactive territories/countries without CPIA data. It excludes IBRD only countries for which the CPIA scores are not currently disclosed (World Bank, 2013, p. 1).

Thus one can argue that the World Bank list better reflects conflict and post-conflict countries. In contrast, the OECD 'non-official' list conflates conflict/post-conflict countries with countries that might not, under certain definitions, fit into such a group – by using the 2009 World Bank list and adding to this some very populous countries that are included in the Failed States Index of the US think-tank, the Fund for Peace:

The list of countries in fragile situations used for this analysis (neither an official DAC list nor an official definition)… is a compilation of two lists: the Harmonised List of Fragile Situations… and the 2009 Fund for Peace Failed States Index. The list includes Pakistan, Nigeria and Bangladesh, which together represent one-third of the total population living in these 45 countries (OECD, 2013a, p. 1)

Thus the primary difference between the OECD and the World Bank lists, in terms of poverty estimates, becomes about the adding of these three populous countries as if one would say the problems of countries like Pakistan, Nigeria and Bangladesh are the same as conflict/post-conflict countries such as the DRC. In short, does it make sense to conflate conflict/post-conflict countries with such countries?

Figure 7: Distribution of global $2 poverty to 2030 by income groups, survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios



Source: Authors' own.

Note: LIC and MIC status in 2020 and 2030 estimated as per method outlined in text; Aggregations do not include China and India.

fragile states. We do find that the use of NA means generally has a bias of increasing the proportion of global poverty likely to be found in fragile states and low-income countries in contrast to the use of survey means. However, even using the NA means we are unable to find that remaining world poverty in 2025 will be focused largely in low-income fragile states.

Although the actual text of Kharas and Rogerson (2012), could be interpreted as arguing that global poverty will be focused in fragile LICs. One interpretation is, however, that the authors are referring not only to the group of fragile, low-income countries but to low-income countries PLUS other (MIC) fragile states. There is some considerable ambiguity in the report that make it difficult to discern:

> We project that, by 2025, the locus of global poverty will overwhelmingly be in fragile, mainly low-income and African, states, contrary to current policy

> preoccupations with the transitory phenomenon of poverty concentration in middle-income countries (p. 3).
>
> Income stagnation and high fertility rates in selected low-income and fragile countries re-establish them as the main locations of global poverty (p. 5)
>
> …while there is some debate today about how many of the world's absolute poor still live in middle-income countries (MICs), the dynamics of growth and demographics suggest that, by 2025, most absolute poverty will once again be concentrated in low-income countries (LICs)" (p. 5).
>
> …by 2025, most absolute poverty will once again be concentrated in low-income countries (LICs) (p. 5)
>
> This trend is already visible: for the first time, there are probably (sic) more poor people today in fragile states than in non-fragile states (p. 7)

All of which makes it quite difficult to be clear what group of countries are being referred to for certain. Further, one cannot determine exactly what is meant by 'selected' countries. The 'top 10' countries listed in an annex (p. 32) account for 333m $2 poor but it is not clear what the other countries are that account for world poverty in 2025 outside these ten countries.

Thus, taking the broadest possible meaning, one could test what the 2025 poverty numbers look like across scenarios if one aggregates all current LICs *PLUS* all current fragile states (LIC and MIC).

If one takes all current LICs plus all fragile countries (see annex tables A4 and A5), that combined group of over 80 countries could be home to as little as a third of world $2 poverty (pessimistic growth, current inequality trends, survey means) or as much as 90% of world $2 poverty in 2025 (optimistic growth and best ever distributions, NA means).

In almost half of all the scenarios poverty in stable MICs remains around half of all world poverty and the poverty headcount in stable MICs could range from 100m to 1.5bn. *That changes in assumptions can produce such large differences seems too important a point to miss.*

There are three further complications. First, the poverty line in Kharas and Rogerson is unadjusted so it is lower than $2. However, even if one uses a lower poverty line of $1.25, stable MICs might still account for up to 55% of world poverty in 2025 (pessimistic growth, current inequality trends, survey means), but on the other hand stable MICs could be as low as 7% (optimistic growth and best-ever distributions, NA means). Again demonstrating a level of difference that is so startling it is impossible to ignore. And given, second, that we also find that the use of NA means consistently increases the proportion of global poverty in low income countries and in fragile states one might suggest that caution and some recognition of the bias inherent in the method of analysis is needed before using any single forecast method and scenario as the basis for proposals on future aid allocations.

Third, if one uses the LICs that will be LICs in 2025 or the World Bank's fragile states lists world poverty in 2025 drops significantly in the 'all LIC PLUS all fragile states' group across all estimates and consequentially global poverty shifts back to stable MICs in all scenarios, meaning the choice of fragile states list taken and whether one takes note that some LICs will be MICs in 2025 is deterministic too.

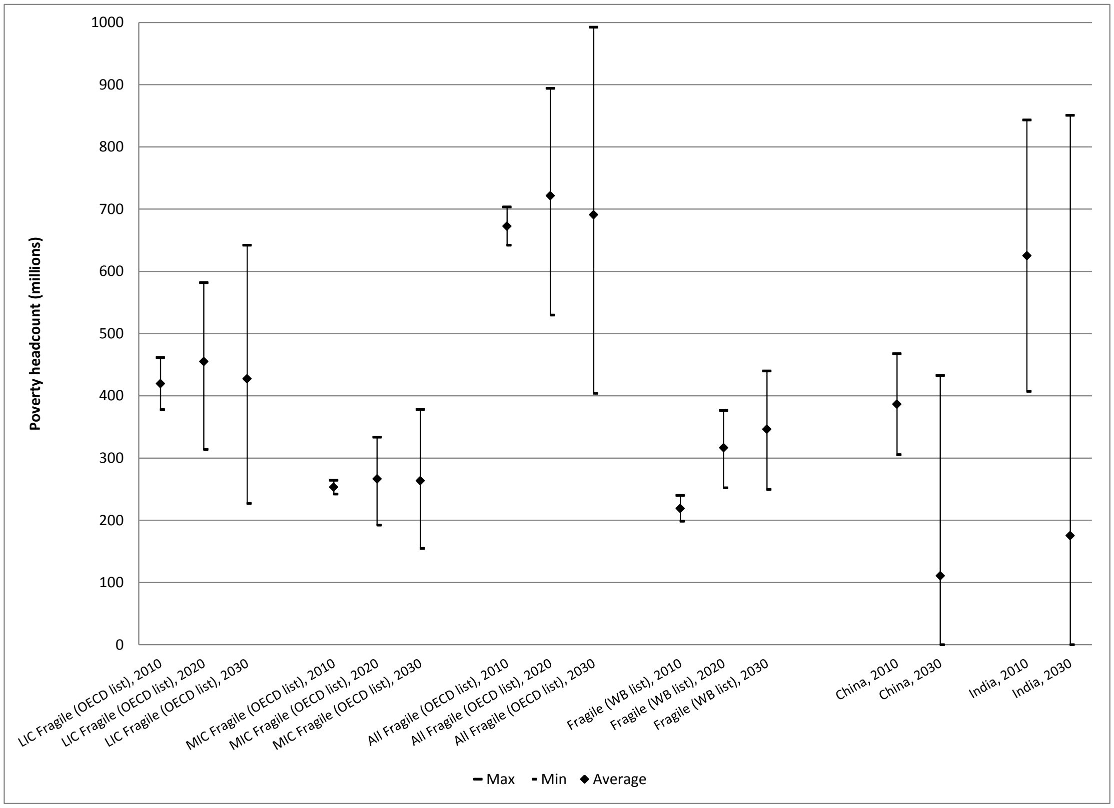
In short, an emphasis on every developing country other than stable MICs, seems to rather overlook that in 2025 it is quite possible that around half or more of global poverty might still be found in stable MICs – particularly if one bases poverty estimates on survey means as used by the World Bank. That the estimates can be so different is startling.

At the very least this illustrates the pitfalls of proposing policy redirection based on analyses that do not rigorously explore their own biases and sensitivities, leading to the danger that a method biased towards a particular group of countries is used, without awareness and consideration of its inherent bias and uncertainties, to argue that the aid industry should be restructured around those same countries.

If we take current categorisation of states (and therefore ignore the possibility that some states will graduate by 2025 from their low-income or fragile status), we estimate, using the longer OECD list, that at most 50% of global $2 poverty might be in current fragile LICs in 2025 but the figure is more likely to be between 25% and 40% (up from around 20% in 2010). And, if recent inequality trends continue, current low-income fragile states could still account for just one-fifth of global poverty in 2025. If all (i.e. LIC plus MIC) fragile states are included their share of global $2 poverty in 2025 rises to 70% under one scenario although a figure of 40% to 60% might be more likely (still an increase on the current 35%). When we look at figures for the $1.25 line we find this does not much alter our conclusions, namely that LIC fragile states are unlikely to account for much more than 50% and all fragile states are unlikely to account for more than 70% of global poverty on any scenario. Of course if states graduate from LIC or fragile status by 2025 then these percentages would be reduced. Across the 12 scenarios the average for $2 poverty in fragile MICs is 21% of global poverty (up from around 12% in 2010), and a range of 15% to 30% seems likely.

In every case the survey means produce lower proportions and the NA means generate higher proportions of global poverty in fragile LICs. Use of survey means typically reduces the share in fragile LICs by 10 percentage points or more (i.e. a 50% figure from survey means becomes 40% or less with NA means). In short, the use of consumption means from

Figure 8: Proportion of global poverty in fragile states, $2 poverty line, to 2030, survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios



Source: Authors' own.

Note: Fragile State and Income Category status of countries in 2020 and 2030 as current lists; aggregations do not include China and India.

national accounts has a bias of increasing the proportion of world poverty likely to be found in low-income fragile states in contrast to the use of survey means as used by the World Bank. The difference between survey and NA means is much less pronounced for fragile MICs.

Since around one-third, and in some scenarios quite possibly more than a half, of global poverty in the coming decades will be in countries that are not currently fragile (irrespective of Income Category) it seems premature to argue that aid should be refocused predominantly onto low-income and fragile countries (Figure 8 and Table A3). There does not seem to be a case here therefore for distinguishing between MIC and LIC fragile states – the range of results across the scenarios would suggest caution in restructuring the aid industry on analyses based on just one scenario or set of model assumptions. Instead what needs to be noted is that while global poverty is generally expected to fall by 2030, poverty headcounts in fragile countries look like they will not be part of these falls. There may therefore be a case for refocusing aid onto these fragile states while being careful about which 'fragile states'. In this regard, the 34 countries in the World Bank's 'harmonised list of fragile situations' may be more useful than the OECD list as in these states the poverty headcounts are forecast to rise under all scenarios (Figure 8).

Finally, an alternative approach may be to consider the possible location of global poverty by 'country convergence groups' based on the OECD (2010, p. 35) concept of a 'four-speed world' (or a three-speed developing world) that categorises countries based on average per capita growth rates for 2000–2010 as follows:

- Affluent countries – these are HICs;
- Converging countries – countries with GDP pc growth more than twice OECD HIC growth rate;
- Struggling countries – countries with GDP pc growth less than twice OECD HIC growth rate and MIC at end of period;
- Poor countries – countries with GDP pc growth less than twice OECD HIC growth rate and LICs at end of period.

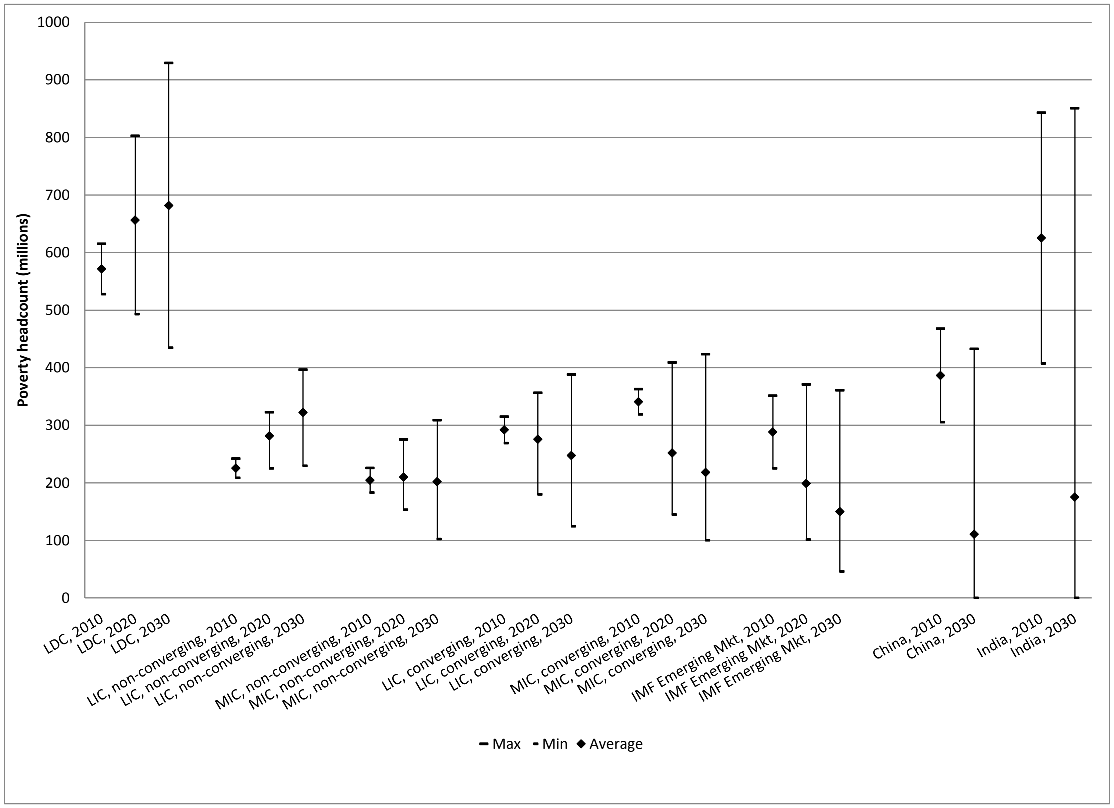
This produces a large list of more than 80 countries (of which 63 have poverty data) that are 'convergers' in the 2000–2010 period (OECD, 2012, p. 256–8). Figure 9 shows estimates for these groups and also for the UN Least Developed Country group (48 countries) and a group that form a non-official list of the IMF's Emerging Market Economies group (48 countries also, taken from Ghost et al., 2009). (Again, poverty numbers for China and India are shown separately and not included in the aggregated categories on Figure 9).[27]

For the UN Least Developed Country group (LDCs), $2 poverty headcounts are forecast to reduce (from about 500m or 600m in 2010) by at most 100m by 2030. This would be under the optimistic growth scenario. If growth is closer to the pessimistic scenario then LDC poverty is likely to rise, perhaps by as much as 250m to 300m. The LDC categorisation may therefore still form a useful starting point for considering aid priorities. Figure 9 also suggests that, based on current income categories, the LIC non-converging countries are likely to see their poverty headcounts increase by 2030. MIC non-converging countries will struggle to reduce poverty and could also see their poverty headcounts rise. LIC convergers are likely to see poverty headcounts fall but it is not certain that they will do. MIC

27 Sum of the convergence and non-convergence rows for the OECD list in the annex tables are less than the global totals because there are 19 current L/MIC countries that do not appear in the OECD list of affluent-converging-struggling-poor countries.

convergers currently account for more poverty than the LIC convergers but it seems MIC convergers are rather more likely, than LICs, to see their headcounts fall by 2030.

Figure 9: Distribution of global $2 poverty to 2030 by convergence groups, survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios



Source: Authors' own.

Note: as described in the text, aggregations do not include China and India.

5. Conclusions

A set of recent papers has sought to make poverty projections into the future of global poverty. These have significant policy implications because it is only by understanding both the future scale and anticipated locations of poverty that properly informed debates can be had on the scale and objectives of future aid. We add to those papers by introducing a new model of poverty, inequality and growth. We would argue that any attempt to make projections about poverty ought to be based on presenting scenarios and ranges of possible outcomes, including estimates by both national accounts and survey means, so as to avoid deriving policy on limited analyses that fail to recognise the scale of bias built into different modelling approaches. Furthermore, the failure to include in the discussion potential changes in inequality and their impact on poverty could mean estimates of poverty levels in the future are very misleading. It is plausible that $1.25 and $2 global poverty will reduce substantially by 2030. However, this is by no means certain. Different methods of calculating and forecasting poverty numbers give very different results as do changes in inequality.

Uncertainties over future, and even current, poverty levels are especially high for India and China. While it is likely that poverty in those countries will reduce dramatically by 2030 it is difficult to have much certainty over just how large those reductions will be. There are various reasons for this but in India the predominant one is the widening discrepancy between NA and survey means. The use of NA means rather than survey means dramatically reduces poverty estimates for India, even after adjustments have been made to global poverty lines to allow for the systemic difference between NA and survey means. In China the predominant reason is the scale of changing inequality and uncertainty over whether current inequality trends will continue at the same rate in the future. Because of these uncertainties it is possible to conceive, under different growth scenarios and different assumptions about future inequality, that $2 poverty could be eradicated in India and China by 2030 or that it could be at or above current levels.

If these two countries are separated out and treated as 'special cases', then the trends elsewhere in the world indicate that in 2030 poverty will have fallen across Asia but would almost certainly have risen substantially in sub-Saharan Africa, to the extent that sub-Saharan Africa will come to dominate global poverty headcounts. Poverty in Latin America and the Middle East will remain at relatively low levels but is unlikely to reduce much from those levels.

Looking to income classifications, currently most poverty is in middle-income countries – so much so that even when China and India are removed from the picture poverty is still more or less evenly divided between LICs and MICs. Even with those two countries excluded the forecast poverty reductions in the remaining MICs are not so large, nor so certain, as to justify in themselves the view that poverty in the future will be a matter for LICs primarily. In fact, once recategorisations are taken into account it seems that poverty outside India and China will remain roughly evenly distributed across MICs and LICs.

Looking to other possible classifications that might assist in developing aid policy, there is some sign that the fragile classification is useful as it seems to identify a set of countries where poverty reduction may well prove difficult. However we find little sign that this problem will be confined to LIC fragile states – poverty reduction seems equally unlikely in the MIC fragile states. It may be that the World Bank's shorter list of fragile states that emphasises conflict/post-conflict countries is more useful but even then the UN's widely used LDC categorisation might be just as useful or more so.

We do, however, find some evidence that a 'multi-speed world' categorisation, perhaps in combination with income category, might be useful as a way to identify and prioritise countries likely to have difficulty reducing poverty. We find here that LICs that are non-converging ('poor' or 'struggling' in the OECD classification) are likely to experience rising poverty by 2030. MICs that are non-converging are likely to struggle to reduce poverty. LICs that are converging may well experience some poverty reduction and MICs that are converging will probably experience the most poverty reduction (again this excludes India and China which are considered to merit individual treatment and consideration as 'special cases' in view of their size and rapid growth). In all cases, the size of any poverty reduction (or even whether it is a reduction or an increase) is highly dependent on future economic growth and inequality trends.

One question the exercise of this paper raises is to what extent do changes in inequality affect poverty projections? It is surprising just how much difference changes in inequality could make to global poverty in 2025 and beyond – to both the numbers of poor people and the costs of ending poverty. Forecasts of global poverty in 2025 and beyond are sensitive to assumptions about inequality. In one scenario (pessimistic growth and survey means) we estimate that the difference between poverty estimated on current inequality trends versus a hypothetical return to 'best ever' inequality for every country could be an extra billion $2 poor people in 2030. Taking the scenario of optimistic economic growth, $2 poverty could fall from around 2 billion today to 600m by 2030 – if every country returned to 'best ever' inequality. However, if recent trends in inequality continue it could rise so that (based on survey means analysis and if growth is pessimistic) there could be an extra 400m $2 poor in 2030 compared to today.

Under none of our scenarios does SSA $2 poverty reduce significantly and under most it rises. Poverty is, however, likely to have reduced across Asia by 2030, probably very dramatically, but the actual extent of the reduction will depend on the amount of growth and how this interacts with changing inequality. Under the pessimistic growth scenario current poverty levels for East and South Asia combined may be halved (assuming that lower economic growth comes without increasing inequality) but under optimistic growth, poverty in Asia could be mostly eradicated (although this depends in China on curbing rising inequality and in India on seeing NA growth flowing through more strongly into survey mean growth). In the rest of the world poverty will remain around 10% of the global total but it is also likely to prove difficult to eradicate or reduce.

Estimates of where the world's poor will be located depend therefore not only on whether survey or NA means are used to estimate poverty but also on assumptions about changes in inequality. In 2030 if current inequality trends continue and growth is strong, there could be a doubling of the proportion of global poverty in sub-Saharan Africa (by survey or NA means) and a corresponding fall in the contribution of South Asia, and of India in particular, to global poverty. On the other hand, if inequality were to return to 'best ever' distributions for each country and growth was strong, then the shift of global poverty to sub-Saharan Africa would be far more pronounced with two-thirds or perhaps three-quarters or more of global poverty in the region by 2030 and corresponding shifts away from South Asia.

In short, under all our scenarios in 2030 we can expect sub-Saharan Africa to remain close to or above current levels and to dominate poverty headcounts. We can also expect a wide range of possible global poverty totals. Global $2 poverty will most likely fall substantially from current levels of around 2 billion today, perhaps to almost as low as half a billion. But the fall is likely to be much less than this and it could even rise to close to 2.5 billion. Much of this depends on how much economic growth occurs and on how efficiently it is converted into poverty reduction in East and South Asia. Depending on what happens there, in 2030 sub-Saharan Africa might account for anything between one-third and three-quarters of global $2 poverty.

There are obviously major uncertainties inherent in these analyses and forecasts, but also some dominant themes that emerge and that justify at least attempting to make these sorts of analyses and forecasts of global consumption distributions. In conclusion, we would argue that despite all these uncertainties in the modelling there is evidently benefit in using the available data to attempt to estimate global poverty in the future as long as one's approach recognises these uncertainties and the wide range of possible estimates that might be derived from the various different ways of allowing for them. This means that while we must always treat the outputs from such a modelling exercise with caution and scepticism, we should not only strive to make models that are as robust as we can make them, but also use those models to develop a range of possible outputs that reflect the inherent uncertainties and assumptions involved. That way even if we have doubts over absolute poverty figures, we should be able to have more understanding of the significance of differences, the overall direction of trends and the robustness of any results that are feeding into policy deliberations.

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DATA ANNEX

Table A1. Poverty, $1.25, 2030, millions

Inequality	2010		Extrapolated current trends				Static inequality				'Best-ever' distribution			
Growth			Pessimistic		Optimistic		Pessimistic		Optimistic		Pessimistic		Optimistic	
Mean	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Current LICs	324	426	453	584	224	342	428	574	229	345	405	557	213	327
Least Developed Countries	338	439	512	654	280	404	496	640	287	402	470	621	268	381
All Fragile States	352	421	473	596	204	315	477	582	212	321	421	535	182	287
LIC Fragile States	233	318	298	405	107	206	281	404	126	224	262	390	115	212
LIC and non-converging	154	196	266	316	117	208	256	320	132	218	248	313	124	210
Conflict/Post-Conflict Countries	130	166	263	323	147	233	257	317	160	228	248	308	153	220
MIC and non-converging	93	68	83	94	48	54	133	104	52	57	117	95	42	46
MIC Fragile States	120	103	175	191	96	109	196	178	85	98	158	144	67	75
LIC and converging	162	216	173	236	104	129	163	230	93	121	149	221	86	112
Current LMICs	613	240	579	243	114	130	330	225	103	118	251	178	77	87
Current UMICs	160	236	277	308	98	118	35	28	16	14	29	26	15	13
All current MICs	773	476	856	550	211	248	365	253	119	132	280	205	92	100
All non-Fragile MICs	654	373	681	359	115	139	168	75	33	34	121	60	25	25
MIC and converging	679	407	772	456	163	194	232	148	67	75	163	110	50	54
IMF Emerging Market Economies	649	328	650	317	100	120	172	35	18	16	126	29	16	15
LICs in 2030			448	591	215	301	438	584	218	291	426	576	214	287
MICs in 2030			849	532	213	281	343	229	122	177	247	172	84	132
No of LICs in 2030			30	30	16	16	30	30	16	16	30	30	16	16
No of MICs in 2030			97	97	89	89	97	97	89	89	97	97	89	89
Global total	1097	902	1309	1134	435	590	793	827	348	477	685	762	305	427

Table A2. Poverty, $2, 2030, millions

Inequality	**2010**		**Extrapolated current trends**				**Static inequality**				**'Best-ever' distribution**			
Growth			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
Mean	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Current LICs	497	586	684	845	406	539	664	840	378	534	634	818	361	520
Least Developed Countries	528	615	756	929	475	620	752	924	456	613	720	903	435	595
All Fragile States	642	703	830	992	426	551	853	987	452	561	791	929	404	515
LIC Fragile States	378	461	489	642	256	364	475	637	239	370	450	617	227	360
LIC and non-converging	209	242	349	394	252	309	342	396	237	315	338	395	229	309
Conflict/Post-Conflict Countries	198	240	371	440	263	331	365	438	258	327	358	437	250	317
MIC and non-converging	226	183	286	225	102	114	309	256	173	142	292	244	153	125
MIC Fragile States	264	242	341	350	169	187	378	350	213	191	341	312	177	155
LIC and converging	269	315	293	388	143	202	287	382	134	199	261	361	124	192
Current LMICs	1345	831	1411	610	383	241	946	572	267	244	838	484	218	193
Current UMICs	397	553	518	511	210	237	118	179	44	37	70	78	36	34
All current MICs	1743	1384	1929	1121	592	477	1064	752	311	282	908	562	254	228
All non-Fragile MICs	1478	1142	1588	770	423	291	686	402	98	90	567	250	77	73
MIC and converging	1511	1193	1641	892	490	363	754	492	138	140	614	315	100	103
IMF Emerging Market Economies	1499	1100	1578	725	392	248	731	372	123	62	620	223	102	50
LICs in 2030			601	769	323	390	600	771	302	371	592	772	299	367
MICs in 2030			1983	1173	659	613	1105	793	372	428	927	582	301	364
No of LICs in 2030			30	30	16	16	30	30	16	16	30	30	16	16
No of MICs in 2030			97	97	89	89	97	97	89	89	97	97	89	89
Global total	2241	1971	2618	1969	999	1017	1730	1592	689	816	1542	1380	614	748

Table A3. Proportion of global poverty (%) in fragile states (OECD 45 countries unless stated), $2 poverty line, in 2025 and 2030, survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios

Inequality	**2010**		**Extrapolated current trends**				**Static inequality**				**'Best-ever' distribution**			
Growth			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
Mean	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
2025														
LIC Fragile States	16.9	23.4	19.0	31.8	24.4	38.3	24.8	36.3	32.5	46.0	27.0	41.3	34.5	49.1
MIC Fragile States	11.8	12.3	13.4	17.2	16.4	18.4	19.0	19.7	26.0	23.0	19.6	20.6	25.4	20.9
All Fragile States	28.6	35.7	32.4	49.0	40.8	56.7	43.7	55.9	58.4	69.0	46.6	61.9	59.8	70.0
World Bank 'Fragile Situations'	8.8	12.2	13.8	21.1	21.8	29.9	18.0	24.2	29.3	35.6	20.1	28.2	32.6	38.7
2030														
LIC Fragile States	16.9	23.4	18.7	32.6	25.6	35.8	27.5	40.0	34.7	45.3	29.2	44.7	37.0	48.1
MIC Fragile States	11.8	12.3	13.0	17.8	17.0	18.4	21.9	22.0	30.9	23.5	22.1	22.6	28.8	20.7
All Fragile States	28.6	35.7	31.7	50.4	42.6	54.1	49.3	62.0	65.6	68.8	51.3	67.3	65.8	68.8
World Bank 'Fragile Situations'	8.8	12.2	14.2	22.3	26.3	32.6	21.1	27.5	37.4	40.1	23.2	31.7	40.6	42.4

Table A4. Estimates of $1.25 poverty in 2010 and 2025 by various scenarios (millions and % global total)

Inequality	2010		Current trends				Static inequality				'Best-ever'			
Growth			Pess.		Opt.		Pess.		Opt.		Pess.		Opt.	
Mean	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA
Poor (millions)														
LIC Fragile states	233	318	283	400	134	230	278	395	142	241	255	379	132	231
Current LICs	324	426	389	559	223	357	409	547	241	358	382	528	225	343
All fragile states	352	421	436	571	227	335	457	555	234	339	397	507	198	304
Total (Current LICs plus fragile MICs)	444	529	542	730	317	463	588	708	333	456	524	656	291	416
% world poverty														
LIC Fragile states	21.2	35.3	23.5	38.7	30.6	39.2	33.6	48.3	38.0	48.6	35.9	52.9	41.0	51.7
Current LICs	29.5	47.2	32.3	54.1	50.9	60.9	49.4	66.9	64.4	72.2	53.8	73.6	69.9	76.7
All fragile states	32.1	46.7	36.2	55.2	51.8	57.2	55.2	67.8	62.6	68.3	55.9	70.7	61.5	68.0
Total (Current LICs plus fragile MICs)	40.5	58.6	44.9	70.6	72.4	79.0	71.0	86.6	89.0	91.9	73.8	91.5	90.4	93.1
Memo items														
Stable MICs														
Poor (mills)	654	373	664	303	122	123	239	110	41	40	186	61	31	31
% total	59.6	41.4	55.1	29.3	27.9	21.0	28.9	13.4	11.0	8.1	26.2	8.5	9.6	6.9
LICs in 2025														
Poor (mills)			407	581	226	344	431	562	241	329	407	548	230	318
% total			33.7	56.2	51.6	58.7	52.1	68.7	64.4	66.3	57.3	76.4	71.4	71.1
WB Fragile states														
Poor (mills)	130	166	238	300	154	224	232	289	157	218	222	283	150	210
% total	11.9	18.4	19.7	29.0	35.2	38.2	28.0	35.3	42.0	44.0	31.3	39.5	46.6	47.0

Table A5. Estimates of $2 poverty in 2010 and 2025 by various scenarios (millions and % global total)

Inequality	2010		Current trends				Static inequality				'Best-ever'			
Growth			Pess.		Opt.		Pess.		Opt.		Pess.		Opt.	
Mean	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA
Poor (millions)														
LIC Fragile states	378	461	476	618	299	424	467	612	291	420	446	594	268	404
Current LICs	497	586	605	799	405	587	638	792	426	577	612	774	399	559
All fragile states	642	703	813	951	500	627	825	944	524	629	771	891	466	576
Total (Current LICs plus fragile MICs)	761	828	942	1132	606	791	996	1124	659	786	936	1071	596	731
% world poverty														
LIC Fragile states	16.9	23.4	19.0	31.9	24.4	38.3	24.8	36.3	32.4	46.1	27.0	41.3	34.4	49.1
Current LICs	22.2	29.7	24.1	41.2	33.0	53.1	33.8	46.9	47.5	63.3	37.0	53.8	51.2	67.9
All fragile states	28.6	35.7	32.4	49.0	40.7	56.7	43.7	56.0	58.4	69.0	46.6	61.9	59.8	70.0
Total (Current LICs plus fragile MICs)	34.0	42.0	37.5	58.4	49.4	71.5	52.8	66.6	73.5	86.2	56.6	74.4	76.5	88.8
Memo items														
Stable MICs														
Poor (mills)	1478	1142	1564	804	619	314	888	561	238	125	717	369	182	92
% total	66.0	57.9	62.3	41.5	50.4	28.4	47.1	33.3	26.5	13.7	43.3	25.6	23.4	11.2
LICs in 2025														
Poor (mills)			607	799	342	469	647	790	367	453	625	774	356	449
% total			24.2	41.2	27.9	42.4	34.3	46.8	40.9	49.7	37.8	53.8	45.7	54.6
WB Fragile states														
Poor (mills)	198	240	347	409	268	330	339	407	263	324	333	405	254	318
% total	8.8	12.2	13.8	21.1	21.8	29.8	18.0	24.1	29.3	35.5	20.1	28.1	32.6	38.6

Table A6. Distribution of global poverty, $2 poverty line, in 2030 by regions, by survey means (S) and national accounts (NA) means, pessimistic/optimistic growth and three inequality scenarios

Inequality	**2010**		**Extrapolated current trends**				**Static inequality**				**'Best-ever' distribution**			
Growth			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
Mean	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
2030 headcounts (millions)														
East Asia and Pacific	500	602	542	525	204	220	109	189	16	13	63	86	11	7
Latin America and Caribbean	69	74	108	63	32	40	64	69	36	39	51	59	28	33
Middle East and North Africa	50	47	90	75	50	52	81	76	50	54	76	75	47	50
South Asia	1089	621	1052	319	183	47	679	289	82	51	604	234	71	46
sub-Saharan Africa	507	598	798	963	520	651	783	951	503	654	740	914	457	611
China	305	467	367	433	169	203	35	105	0	0	0	16	0	0
India	843	407	851	119	151	0	441	90	2	0	389	59	0	0
Total	2241	1971	2618	1969	999	1017	1730	1592	689	816	1542	1380	614	748
2030 (%age of global total)														
East Asia and Pacific	22.3	30.5	20.7	26.7	20.4	21.6	6.3	11.9	2.3	1.6	4.1	6.2	1.8	0.9
Latin America and Caribbean	3.1	3.7	4.1	3.2	3.2	3.9	3.7	4.3	5.2	4.8	3.3	4.3	4.6	4.4
Middle East and North Africa	2.2	2.4	3.4	3.8	5.0	5.1	4.7	4.8	7.3	6.6	5.0	5.4	7.7	6.7
South Asia	48.6	31.5	40.2	16.2	18.3	4.6	39.2	18.2	11.8	6.3	39.2	17.0	11.5	6.2
sub-Saharan Africa	22.6	30.4	30.5	48.9	52.0	64.1	45.3	59.8	73.0	80.2	48.0	66.3	74.4	81.6
China	13.6	23.7	14.0	22.0	16.9	19.9	2.0	6.6	0.0	0.0	0.0	1.1	0.0	0.0
India	37.6	20.7	32.5	6.1	15.1	0.0	25.5	5.6	0.3	0.0	25.2	4.3	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table A7: Total Poverty Gap at $1.25, 2030 ($bn 2005 PPP)

Inequality	**2010**		**Extrapolated current trends**				**Static inequality**				**'Best-ever' distribution**			
Growth			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
Mean	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Current LICs	62	126	86	175	37	85	87	182	41	98	82	173	38	91
Least Developed Countries	64	129	100	197	49	104	101	200	52	113	94	191	48	106
All Fragile States	55	111	76	161	28	77	79	164	33	84	68	149	30	77
LIC Fragile States	39	89	45	111	12	51	49	120	19	61	46	115	18	57
LIC and non-converging	31	66	45	101	14	52	49	109	20	61	47	105	18	58
Conflict/Post-Conflict Countries	26	55	48	104	23	64	51	104	27	67	48	100	26	65
MIC and non-converging	12	16	15	24	8	12	18	24	7	12	14	20	6	9
MIC Fragile States	15	23	32	50	16	26	29	44	14	22	22	34	12	19
LIC and converging	30	57	40	68	23	32	37	69	21	35	34	65	19	31
Current LMICs	68	39	71	62	19	31	40	55	16	27	29	41	13	21
Current UMICs	17	41	52	86	11	22	5	6	2	3	5	6	2	3
All current MICs	85	80	123	148	30	53	45	61	18	30	33	46	15	24
All non-Fragile MICs	69	57	92	98	14	27	15	17	5	7	11	12	3	5
MIC and converging	72	64	108	124	23	41	27	37	11	18	19	27	10	15
IMF Emerging Market Economies	66	47	85	87	11	22	12	7	2	3	9	7	3	3
LICs in 2030			94	189	41	82	95	192	43	91	91	186	42	88
MICs in 2030			113	130	25	54	35	47	15	34	22	30	11	24
No of LICs in 2030			30	30	16	16	30	30	16	16	30	30	16	16
No of MICs in 2030			97	97	89	89	97	97	89	89	97	97	89	89
Global total	147	206	210	323	68	138	132	242	60	127	115	220	53	115

Table A8. Total Poverty Gap at $2, 2030 ($bn 2005 PPP)

Inequality	2010		Extrapolated current trends				Static inequality				'Best-ever' distribution			
Growth			Pessimistic		Optimistic		Pessimistic		Optimistic		Pessimistic		Optimistic	
Mean	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA	S	NA
Current LICs	176	344	244	480	121	271	239	482	124	282	225	464	116	268
Least Developed Countries	184	355	276	535	151	320	274	533	154	326	258	513	145	310
All Fragile States	193	352	253	495	112	259	263	495	123	267	234	455	108	243
LIC Fragile States	124	257	153	335	60	171	154	341	68	185	144	327	64	177
LIC and non-converging	81	160	131	252	64	164	133	260	71	174	129	255	67	168
Conflict/Post-Conflict Countries	71	142	135	266	79	184	137	263	85	184	132	257	82	178
MIC and non-converging	56	68	58	87	28	47	78	99	37	51	70	89	31	42
MIC Fragile States	69	95	100	160	53	88	108	154	54	81	90	128	44	66
LIC and converging	90	172	104	203	56	99	99	200	51	101	89	187	47	94
Current LMICs	340	257	345	226	80	108	209	210	66	100	171	169	52	78
Current UMICs	91	206	156	253	53	97	23	47	10	13	18	24	9	13
All current MICs	432	464	500	478	133	205	232	257	76	113	189	193	61	90
All non-Fragile MICs	363	368	400	318	80	117	124	103	22	32	98	66	16	24
MIC and converging	375	394	442	391	105	157	154	157	39	62	119	103	30	48
IMF Emerging Market Economies	363	339	387	284	71	99	127	77	20	16	106	47	17	15
LICs in 2030			239	479	114	230	239	480	115	231	231	472	113	226
MICs in 2030			497	469	136	239	225	246	80	157	175	174	60	125
No of LICs in 2030			30	30	16	16	30	30	16	16	30	30	16	16
No of MICs in 2030			97	97	89	89	97	97	89	89	97	97	89	89
Global total	608	808	745	959	255	476	471	739	200	395	414	658	177	358