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THE FUTURE OF GLOBAL POVERTY IN A MULTI-SPEED WORLD:

NEW ESTIMATES OF SCALE, LOCATION AND COST

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THE FUTURE OF GLOBAL POVERTY IN A MULTI-SPEED WORLD:

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Peter Edward and Andy Sumner*

Various recent papers have sought to make projections about the scale and locations of global poverty in the next 20 to 30 years. Such forecasts have significant policy implications because they are used to inform debates on the scale and objectives of future 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 them. 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, not only do different analysts arrive at very different understandings of the extent and prospects for global poverty but it is also extremely difficult to make meaningful comparisons between different analyses.

In response to this, we introduce here a new model of growth, inequality and poverty that has been developed to allow comparative analyses under a wide range of different input assumptions. After validating the model against World Bank estimates of historical poverty, we then use it 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 \$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 an extra 1 billion \$2 poor people in one scenario. (iii) Where the world's poor people will be located also depends 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 on low-income fragile states on the basis that global poverty will be based in such countries.

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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, 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 classifications. Indeed, we 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.

1 INTRODUCTION

As the world nears the 2015 deadline for meeting the Millennium Development Goals (MDGs), the data available for assessing the current status and trends of progress against MDG 1a — to reduce extreme poverty in 2015 to half of the 1990 level —has been greatly improved. There are two main reasons for this. First, the latest 2005 revision of the International Comparison Program (ICP) has produced new, and arguably much improved, datasets on global purchasing power parity (PPP) exchange rates.[1] And second, largely through the World Bank's 2012 updating of its PovcalNet[2] database, a revised and more comprehensive set of surveys of national income (or consumption) distributions is now available.

In general, it is by combining these datasets (PPP exchange rates and distribution surveys), supplemented by data from the routine updating of country-level macro-economic, or National Account (NA), data —such as the annual measurement of national Gross Domestic Product (GDP) —that estimates of the scale of global poverty and inequality can be made.[3] The availability of these revised datasets, combined with the fast approaching MDG deadline, has reinvigorated interest in trying to reassess current and recent historical levels, locations and trends in global poverty.

Furthermore, as attention turns to the identification and setting of development goals beyond the current 2015 MDG deadline, various recent papers have sought to use these datasets to make poverty projections. While rather limited in number, these papers (e.g. Chandy and Gertz, 2011; Dercon and Lea, 2012; Hillebrand 2009; Karver et al., 2012; Kharas and Rogerson, 2012; Ravallion, 2013; Sumner, 2012) have significant policy implications because it is only by understanding both the future scale and anticipated locations (or 'geography') of poverty that properly informed debates can be had on the scale and objectives of future aid. Unfortunately, these papers have not yielded a consistent picture of future (and even current) global poverty so that various debates exist over issues that have key significance for aid policy in coming decades. For example, there is much debate over whether poverty will become largely confined to the low-income, fragile and slow-developing countries or whether, as emerging economies graduate to higher income categories, we will find that poverty in middle-income countries increasingly becomes a matter of concern for aid and development cooperation policy.

What all these papers share is that their estimates are all derived from the same basic (PPP and distribution) datasets. In other words, the differences that underlie these debates largely arise not because of differences in source data but because of differences in how those data are modelled and how uncertainties in the data are dealt with in that modelling. The differences, therefore, are predominantly methodological, rather than substantive, but the uncertainties they generate can be substantial and do have significant policy implications.

Notably, the different estimates play (in multifarious ways) into current debates about whether aid instruments beyond financial transfers should be considered (e.g. Severino and Ray, 2009; 2010) and/or aid targeting redirected to the poorest countries such as low-income fragile states (e.g. Kharas and Rogerson, 2012), on the basis that global poverty will increasingly be concentrated in those countries while any residual poverty in emerging economies could well become defined as a national rather than an international question.

While many of these papers do make forecasts under varying assumptions concerning future economic growth, typically at country level, it is rare for them also to consider the sensitivity of their estimates of future global poverty to the different assumptions built into their modelling of the underlying relationships between poverty and inequality.

In this paper we present a new model —the GrIP model —to analyse trends in 'Gr'owth, 'I'nequality and 'P'overty. The GrIP model has been developed to facilitate modelling of the growth, inequality and poverty relationship under a range of different modelling assumptions. This allows us to present here a more comprehensive assessment of the range of possible future poverty outcomes resulting not only from different growth forecasts but also from different assumptions about: future changes in inequality assumptions; the use of different poverty lines; and the impact of different fundamental assumptions about how to combine inequality survey data with national account data.

We consider that the GrIP model provides (at least) three improvements over other models. First, it has been built to allow the estimation of national distributions using either survey means (as used by the World Bank in PovcalNet) or NA means (as used by Sala-i-Martin, Kharas-Rogerson and many others). This is a fundamental difference between the two commonly used approaches to poverty modelling and 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 Povcal (February 2012) which covers only 130 countries (none of which are high-income countries), the GrIP model provides a more global model of inequality and poverty by covering 178 countries, representing 97 per cent of the global population.[4]

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 subnational 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 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 from those indicated by the data input to the model.

For these reasons, we believe that the GrIP model provides a robust and rigorous basis from which to derive and compare both current estimates and future forecasts of global poverty and inequality.[5] To demonstrate this we first include a validation of the model, under like-for-like modelling assumptions, against recent World Bank estimates of historical global poverty since 1990 (an important comparison that is often overlooked by some other studies). We then present a range of forecasts for global poverty up to 2040 using a variety of different modelling approaches and growth scenarios.

The central problem that this paper addresses is whether (as some recent papers have argued) the current structure of global poverty, in which the world's poor people today are concentrated in middle-income countries, is a temporary phenomenon that will disappear with economic growth or whether it will persist and remain despite growth —and what implications might the range of forecasts for the scale and location of poverty have for the targeting of international aid. To address this problem, we first (in Section 2) review the methods and forecasts from other papers, paying particular attention to the pitfalls inherent in making future (and past) estimates of poverty and how those recent papers have sought to address these difficulties (or not). Then, in Section 3, we outline the GrIP model, explaining how and why the methods used in the model address these difficulties. Here we also validate the model and then describe the methodology and scenarios used for the projections of future global poverty. Section 4 provides a range of estimates from the GrIP model, under various scenarios and modelling assumptions, for the evolution of global poverty and discusses some of the key implications for aid policy. Section 5 concludes.

2 EXISTING POVERTY PROJECTION MODELS

2.1 POVERTY PROJECTION PITFALLS

At the outset it is important to recognise that estimating global poverty is full of pitfalls. Strident debates exist about the comparability of national surveys of consumption —or income —distribution. Different survey results arise obviously depending on whether one surveys individuals or households and whether one measures consumption expenditure, net income or gross income. Even when surveys purport to address the same measure, differences in survey design and 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.

Even when you have a set of national surveys, the problems do not stop there. 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 US$1/day poverty line), it is necessary to convert national currencies into international currencies. Using market exchange rates to do this is clearly misleading, since the price of a loaf of bread in China is very different from its price in the USA. Purchasing power parity (PPP) exchange rates attempt to rectify this problem, but they are far from ideal.

The latest revision of the International Comparison Program (ICP) attempted to rectify some of the problems here, 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 been reasonably argued that the practical difficulties of the ICP make international comparisons exceedingly hazardous (Deaton, 2010). 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 NA statistics data that do not reflect consumption patterns of people who are poor by global standards (Deaton, 2010).

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. However, as Chandy and Gertz (2011) note, poverty reduction lies at the core of the global development challenge and acts as both the source of motivation and the defining theme for the international development community. Tracking global poverty is, therefore, a matter of global interest and significance such that:

> "While it may be easy for skeptics to dismiss global estimates as an indulgence for statisticians who excel in plucking numbers out of thin air, or bureaucrats who are overly concerned with messaging, the reality is that having a decent grasp on global poverty figures matters" (Chandy and Gertz, 2011: 2).

Furthermore, Deaton —a prominent critic of the ICP —does conclude that:

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

In other words, 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 and the wide range of possible estimates that might be derived from the various different ways of allowing for those uncertainties.

To achieve this while recognising explicitly the difficulties involved, it seems important to try to make the best estimates possible with the available data. This means that while we must always treat the outputs from such a modelling exercise with caution and scepticism, we should both strive to make the model as robust as we can and also use that model 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 be more confident about the significance of differences and the overall direction of trends.

Responding to Deaton's call for a greater recognition of the significance of uncertainties, the functionality built into the GrIP model (outlined above and described in more detail later) enables us to make direct comparisons between estimates based on some of the most significant differences in core assumptions. Notably, most previous estimates of poverty have relied on the use of either survey (S) or national account (NA) means. Comparisons between the impact of these two approaches on estimates of current and historic poverty are not new (see, for example, Ravallion, 2003; Deaton, 2005) and most recently, Dhongde and Minoiu (2013, forthcoming) review in considerable detail and discuss in depth the sensitivity of 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. The decline in poverty over the past decade is found to be robust across methodological choices…[C]onceptually it is difficult to defend replacing the survey mean with the national accounts mean to anchor relative distributions from surveys… Although nationally representative surveys are, in our view, a better and more direct source of information on private consumption, we believe that neither of these estimates is unbiased, but both are plausible. Our sensitivity analysis reveals that global poverty estimates vary not only in terms of the proportion of the poor, and correspondingly the number of poor, but also in terms of the rates of decline in poverty. Poverty estimates based on surveys are higher than those based on national accounts and do not tend to converge in countries with higher income" (Dhongde and Minoiu, 2013: 1 and 11).

We, like Dhongde and Minoiu, find the use of different means leads to significantly different estimates in the scale of global poverty.[6] That this is the case is almost self-evident, since NA means are systemically higher than survey means (as we discuss later). 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. First, 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 that we identify later —fail to 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 —or 'geography' —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

2.2 POVERTY PROJECTIONS BASED ON SURVEY MEANS

Of course these uncertainties are substantially increased when one moves from analysis of historical data to forecasting future poverty numbers. Notably, assumptions about future growth rates and changes in national distributions (whether of income or consumption) can make significant differences to projections of future patterns of global poverty. Particularly significant are the assumptions applied to the 15 to 20 countries where 80 per cent of the world's poor people at $1.25 and $2 poor/day live.[7]

It is worth noting that these lists include India and China, where there are major doubts about the comparability of the surveys; Ghana, where NA data have been revised substantiall;[8] and Nigeria too, where NA data will be revised substantially. Notwithstanding these difficulties, several recent papers have sought to make forecasts, but in doing so they have often made significantly different modelling assumptions so that it becomes difficult to treat all these forecasts as directly comparable. To explore this, we discuss the results and approach of various of these papers next.

The first of the recent set of papers to make global poverty projections (and trigger others to do so) is that of Chandy and Gertz (2011), who project poverty to 2015 using the World Bank's PovcalNet software (which uses survey means) to generate estimates of poverty headcount and poverty gap for 119 countries for 2005–2015. This covers 5.5 billion people or 95 per cent of the **developing** world (98 per cent of population and 79 of 104 middle-income countries; 85 per cent of population and 33 of 40 low-income countries when the study was done). They take the most recent survey data from PovcalNet —or from the World Bank's World Development Indicators (WDI) if that had more recent data. The survey mean per capita consumption for each country is forecast by applying the Economist Intelligence Unit's (EIU's) forecast growth rates for NA per capita private consumption to the survey mean in PovcalNet (or the mean implicit in the WDI figures). Population numbers are forecast by applying population growth rates from the IMF's World Economic Outlook (WEO) database to WDI population figures.

Poverty forecasts are then produced under the assumption of static inequality —in other words, they assume that future inequality in each country will be unchanged from the most recent survey for that country. This assumption is rather unrealistic but nevertheless standard in almost all projections. Inequality will doubtless change to some extent in each country. However, since it is difficult to anticipate how it will change, it is common to assume static inequality when forecasting poverty (later in this paper we use GrIP to illustrate how different assumptions about future inequality might affect poverty estimates).

Chandy and Gertz (2011) compare their estimates of global poverty in 2005 (historical) and 2015 (forecast) against World Bank estimates for the same years. At that time, the latest World Bank estimates were in the *2011 World Bank Global Monitoring Report* (World Bank, 2011). Subsequently, the *2012 Global Monitoring Report* (Chen and Ravallion, 2012; World Bank, 2012a: 3) declared MDG 1a met **but** revised the Bank's 2005 and 2015 poverty figures. The 2005 data revisions were relatively minor, but the 2015 revised projections were increased notably in all regions except Europe (see Table 1).

Chandy and Gertz's analysis shows good correspondence with the World Bank estimates for 2005 poverty (not surprisingly, since both analyses are derived from PovcalNet and the 2005 figures are historical rather than forecasts), but the 2015 forecasts diverge significantly in some regions. In particular, Chandy and Gertz forecast much faster reductions in poverty in China and India than did the World Bank —even before the Bank later revised its forecasts upwards. Why is this?

The only explanation can be differences in the way the underlying data, which are the same is both analyses, are dealt with in the modelling. Identifying the precise source of the difference is difficult, but the principal issue is probably that in the cases of India and China the World Bank discounts growth projections (which are derived from NA forecasts) before applying them to survey means (see below). This would make a significant difference in the estimates, although three other possible contributory factors may further compound the difference: (i) differences arise as a result of assuming static inequality and high growth (see Chandy and Gertz, 2011: 12). In contrast, (ii) the World Bank's figures use dynamic inequality modelling derived from projections for: demography based on ageing and shifts in the skill composition of the population; changes in the sectoral composition of employment; and economic growth, including changes in relative wages across skills and sectors (for further details, see Bussolo, De Hoyos and Medvedev, 2008). Or (iii) it could be due to Chandy and Gertz's treatment of urban and rural poverty estimates for China and India (2011: 16) which incorporate population growth rates from the UN Urbanization Prospects database.

TABLE 1

Number of Poor People in Millions for $1.25 Poverty Line

	2005			2010	2015		
Region	**Chandy and Gertz**	**World Bank (GMR 2011)**	**World Bank (GMR 2012)**	**Chandy and Gertz**	**Chandy and Gertz**	**World Bank (GMR 2011)**	**World Bank (GMR 2012)**
East Asia	304.5	316.2	332.1	140.4	53.4	119.0	159.3
Of which China	*207.3*	207.7	211.9		*4.1*	66.1	
Europe and Central Asia	16.0	17.3	6.3	8.4	4.3	5.8	1.4
Latin America and Caribbean	45.0	46.1	47.6	35.0	27.3	29.1	33.6
Middle East and North Africa	9.4	11.0	10.5	6.7	5.4	4.8	9.7
South Asia	583.4	595.6	598.3	317.9	145.2	379.3	418.7
Of which India	*474.3*	455.8			*91.6*	276.8	
Sub-Saharan Africa	379.5	390.6	394.9	369.9	349.9	344.7	397.2
World (developing only)	1337.8	1376.7	1389.6	878.2	585.5	882.7	1019.9

Sources: Chandy and Gertz (2011). Figures in italics are derived from data in text (p. 12) combined with population figures as used in GrIP. World Bank (2011, 2012a). Chen and Ravallion (2010).

With poverty due, according to their estimates, to be virtually eliminated in China by 2015 and in India probably just a few years later, Chandy and Gertz argue that "aid donors must adapt to the evolving poverty landscape and update their policies and programming to reflect current needs and priorities" and that, therefore, they "should be focusing their attention over the medium term [on] sub-Saharan Africa and fragile states" (ibid.: 13) —suggesting that poverty forecasts are intended to influence policy.

As late as 2005 almost three quarters of global poverty was still in low-income countries (LICs), but by 2010, following the graduation of India to middle-income (MIC) status in 2007 and then of Nigeria and Pakistan in 2008, LICs accounted for only a third of global poverty, with two thirds being found in MICs (Sumner, 2010; 2012). It should be noted, however, that this is the result largely of the recategorisation of some countries —poor people have not moved. It represents a change in country status and surprisingly low falls in absolute numbers of poor people over the time span (as noted in Sumner, 2012b). Nevertheless, because aid has historically been targeted on LICs by many donors, this does imply that policy changes might be needed if aid is to be targeted on the countries where most poverty is likely to be found in the future or the country analytical categories may need to be rethought. The interaction of longer-term poverty trends with the recategorisation of country status sets up the tensions of the policy debate as to whether it is necessary to retarget aid more towards MICs or whether the priority focus for aid should remain on LICs while poverty in MICs might come to be seen as a matter of domestic political economy —reflecting, for example, the redistributive preferences of national middle classes and elites, especially at the point where the cost of ending extreme poverty, or even moderate poverty, falls to very low levels of a country's GDP (see Ravallion, 2009; Sumner, 2012a).

According to Chandy and Gertz's forecasts then, as future economic growth reduces poverty, particularly in China and India (two countries that accounted for half the world's poor people in 2005 and both now MICs), the share of global poverty in LICs will steadily rise so that by 2015 almost half of global poverty will, once again, be in LICs. In other words, the current concentration of global poverty in MICs would be a transient phenomenon that will soon pass. If we are to base policy on these sorts of forecasts, then it is useful to pay attention to uncertainties inherent in the forecasts. For example, if one were to rely instead on the World Bank's forecasts, then in 2015 we would find global poverty in the region of 1 billion people (rather than around 600 million), with some 400 million of them still in China and India. Since these are neither LICs nor fragile states, the implications for aid policy may be very different from those proposed by Chandy and Gertz, depending on the objectives of aid policy.

In a different analysis based on survey means, Ravallion (2012) makes poverty projections for global $1.25 poverty in 2017 and 2022 (p. 25) based on the assumption that the "recent success against extreme poverty is maintained" (p. 7). This is done (i) by linear projection (an 'optimistic trajectory') or (ii) by applying World Bank country-level growth forecasts and assuming that mean consumption of households grows in line with GDP growth with no increase in intra-country inequality (an 'ambitious trajectory'). In Ravallion (2012b) 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). However, as 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. Instead, it might be expected that the pace of poverty reduction will start to decline at low levels, making it harder to reach the target. From what we know, we cannot be confident now about when such a slowdown might be expected."

Ravallion (2013) also adds a third 'pessimistic trajectory' which is the (slow) rate of progress of poverty reduction in the developing world outside China in the 1980s and 1990s. In this trajectory, ending $1.25 poverty would take 50 years or so.[9] Recent talk about the possibility of ending extreme poverty in coming decades depends, therefore, on optimistic views on future growth and trends in inequality (see later discussion in Section 4).

Obviously estimates based on forecast scenarios should be treated with care. There are, for example, no guarantees that even the more pessimistic scenarios will be achieved. The risk of systemic shocks, such as the slowdown in growth rates in all countries in 2008/9 or potential impacts of climate change, means that long-term growth rates may be radically different from the forecast scenarios. Nevertheless, assuming that forecast scenarios do approximate to future growth trajectories, there is evidently still a wide range of possible outcomes concerning the length of time it might take to end extreme poverty, and the possibility of even doing so at all, in the face of declining rates of poverty reduction. So, even within the limitations and uncertainties of any forecasts, it does seem that when considering aid policy we ought to be explicit and open about the range of possible outcomes they predict.

Another approach which tries to explore trends across a wide range of growth scenarios has been presented in a series of closely related papers including by one of the co-authors here (see Karver et al., 2012; Sumner, 2012a). As with Chandy and Gertz, and Ravallion, these papers develop forecasts using the World Bank's PovcalNet software. These analyses assume static inequality (that is, the most recent survey distributions are assumed to continue unchanged into the future) combined with forecasts of survey means.[10] Various different assumptions are made to produce a range of growth scenarios used to forecast future survey means. Derived from scenarios earlier developed by Moss and Leo (2011) the papers use IMF WEO growth forecasts (which typically forecast growth for five to seven years into the future) to develop three different longer-term growth scenarios based, in general, on the following kind of pattern:[11]

- Optimistic scenario: assume average national growth rate in WEO is sustained to whatever point in the future;
- Moderate scenario: as 'Optimistic' minus 1 per cent (based on the historic error of IMF projections); and
- Pessimistic scenario: 50 per cent of 'Optimistic' growth.

Two papers (Karver et al., 2012; Sumner, 2012a) present the results of this forecasting exercise. Slight differences exist between these papers due to the use of different periods over which to calculate the WEO average growth rate. Table 2 presents poverty forecasts for 2020 and 2030 using scenarios based on WEO average growth rates for 2009–2016. These figures are taken from Sumner (2012a), where the purpose of the exercise was to ask whether poverty in MICs is transitory.

These estimates indicate a continuing split of world poverty between LICs and MICs up to 2030, if no current LICs become MICs. Sumner (2012a) also estimates which countries might be LICs and MICs in future. Based on those recategorisations, two thirds of $2 (i.e. '$2/day') world poverty is forecast to be in MICs, with the just one third in LICs. While the general pattern is a declining proportion of world poverty in MICs over time, as Sumner (2012a: 22) notes, the rate of decline is much slower than the Chandy and Gertz forecast. Looking at 'extreme' or $1.25 poverty, the forecast under the moderate growth scenario is that 50 per cent of $1.25 poor people would be in LICs in 2020, and 52 per cent in 2030 (all under the assumption that no LICs become MICs). Based on recategorisations, 47 per cent of $1.25 poor people will be in LICs in 2020, falling to 45 per cent in 2030. For comparison, 26 per cent of global $1.25 poverty was in LICs in 2008/9 (Sumner, 2012a: 22). Therefore, and significantly, these forecasts indicate that in 2020 and 2030 half or more of the world's extreme ($1.25) and moderate ($2) poor people may live in MICs—countries where ending poverty may well be becoming domestically affordable (meaning that the total poverty gap amounts to a low proportion of domestic GDP).

The implication of this is that whereas in the past global poverty was a question of poor people in poor countries, and thus aid was an appropriate response, in the future global poverty may well increasingly become a question of national distribution —with the likely consequence that domestic politics may become more important than aid in ending world poverty.

TABLE 2

Estimate of the Global Distribution of $2 Poor People in 2020 and 2030 by Various Growth Scenarios (Numbers are percentage of global $2 poverty total)

	2020			2030		
Scenario	**Pessimistic**	**Moderate**	**Optimistic**	**Pessimistic**	**Moderate**	**Optimistic**
World	100.0	100.0	100.0	100.0	100.0	100.0
East Asia and Pacific	12.6	7.9	7.0	7.5	4.0	2.8
Eastern Europe and Central Asia	0.4	0.4	0.3	0.4	0.2	0.1
Latin America and the Caribbean	4.0	5.3	5.6	4.6	6.3	6.6
Middle East and North Africa	2.6	2.9	2.6	3.4	4.0	3.5
South Asia	41.2	31.9	27.9	30.8	16.5	11.5
Sub-Saharan Africa	39.1	51.6	56.5	53.4	68.9	75.5
Current LICs	31.6	39.7	42.5	40.4	46.5	48.6
Current LMICs	60.0	54.6	51.9	54.9	47.5	45.9
Current UMICs	8.3	5.7	5.7	4.7	6.0	5.6
Remaining LICs in 2020/2030	32.7	33.8	32.5	36.8	35.7	33.0

Source: Sumner (2012a) derived by using method of Karver et al. (2012) and processed from PovcalNet, and WEO (IMF, 2012), based on static inequality. 'Remaining LICs' are LICs expected still to be LICs in 2020 or 2030 (i.e. after allowing for forecast graduation of countries to MIC status by 2020 or 2030).

2.3 USE OF NATIONAL ACCOUNTS VERSUS SURVEY MEANS

As Dhongde and Minoiu (2013) note, the selection of mean (survey or NA) has a significant impact on the size of global poverty estimates (and, we would add, on the location of poverty). The studies discussed above rely on the World Bank's PovcalNet, central to which is that survey distributions are combined with survey means. In all these cases, forecast survey means are derived by applying growth rates for NA per capita metrics to the survey mean in PovcalNet.[12] In contrast, other studies such as Kharas and Rogerson (2012), use NA per capita consumption means directly (i.e. they multiply the survey distribution by a suitable NA mean rather than by a survey mean adjusted in line with NA growth rates).

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: 7, footnote 16) notes that "For most countries, about 90% of the national accounts growth rate is passed onto the survey means, but for India it was only about half". 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.[13] The focus on adjusting growth rates for just these two countries is presumably because they are systematically so important to the global count.

Unfortunately, because of these differences it is difficult to identify reliable correlations when survey means are compared to NA means. Survey means are the estimates of 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). NA means (for example, average GDP or household consumption per capita) 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 expect to see some strong correlation between these means, but in practice reliable correlations are difficult to identify. For example, for current 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).[14] 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 than those derived from the survey mean. Therefore, even when, as we do later with the GrIP model, global adjustments are made for systematic differences between survey and NA means, it is important to recognise that the use of NA means, rather than survey means, necessarily creates a different geography of poverty.

In the debate over whether it is better to rely on survey or NA means when estimating sub- and trans-national[15] 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 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).[16]

So is it better to rely on NA means or survey means? 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 we chose to trust the survey distributions, why would we not also trust the survey means? On the other hand, if NA data show 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 per cent of total household consumption), then should we not include the 'missing millions' of consumption somehow, particularly if we are making comparisons between countries?

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 you use data derived from the survey mean (as is the case with estimates of poverty derived from PovcalNet), then the implicit assumption is that any 'missing millions' between the survey and NA means 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 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 estimating 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 in addition to looking at forecasts derived from PovcalNet (i.e. survey mean with survey distribution) we should also make forecasts derived using NA means and 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 'dollars-a-day' poverty lines applied to PovcalNet-type analyses may need to be increased to determine a broadly comparable poverty line to apply when NA means are used in the analysis. It is important to note that this point that the poverty line **needs** adjustment when NA means are used has not been widely accepted nor practised to date.

2.4 POVERTY ESTIMATES USING NA MEANS

There are various papers that make poverty projections using models that apply NA means directly to the survey distributions.[17] 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: 7).[18] These forecasts indicate that in 2025 global poverty (measured at a $2/day poverty line in 2005 PPP terms) will be predominantly in fragile and conflict-affected states and that poverty in Asia will have reduced sharply so that global poverty is overwhelmingly an African problem. The text of their paper indicates that global poverty will be focused in LICs:

> "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).

…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).

This reference in Kharas and Rogerson to fragile LICs is both strange and misleading as a representation of their data. Their data actually estimate a split of world poverty in 2025 between current LICs and current MICs which is not that far different from the split in Sumner (2012a).[19] Thus their assertion that in 2025 "absolute poverty will once again be concentrated in low-income countries" is puzzling in that it seems to rather understate the expected scale of poverty in MICs.

Notably, their estimate of $2 poverty for 2005 is 1.6 billion, compared to the World Bank's 2.6 billion —in short, 1 billion more people are defined as poor by the World Bank's method (survey mean) than by the Kharas-Rogerson method (NA mean with unadjusted poverty line). In 2015 the World Bank's projection for $2 poverty is for 2 billion (World Bank, 2011: 14), and the Kharas-Rogerson estimate for $2 poverty is a third of that amount or just 700 million people (see Table 3). 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 1 billion $2 poor people in 2008, but the GMR 2011 does not give country-level data).

TABLE 3

Indicative Estimates of Global Poverty at $2/day (billions of poor people)

	1995	2005	2015	2025
Total	2.10	1.58	0.72	0.56
Non-fragile	1.62	1.05	0.27	0.14
Fragile	0.48	0.53	0.45	0.42

Source: Authors' scaling from Figure 1 in Kharas and Rogerson (2012).

TABLE 4

Comparison of Kharas and World Bank Estimates of Global Poverty Headcounts (billions)

	Kharas (2010)	World Bank	World Bank
Poverty line (nominal)	**$2/day**	**$1.25/day**	**$2/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) and World Bank (2011).

Why are these figures so different? It is important to recognise that when Kharas and Rogerson say they are estimating $2 poverty, their poverty line is not comparable with the $2 poverty line applied by the World Bank. This is because the Kharas-Rogerson analysis uses NA means, rather than the survey means, but they do not adjust the poverty line to allow for systematic bias between the two types of mean. This can be illustrated by comparing the Kharas-Rogerson poverty headcounts with World Bank estimates back to 1995 (see Table 4).

It appears that the $2/day line used by Kharas and Rogerson lies currently somewhere between the World Bank's $1.25/day and $2/day poverty lines and is probably rather closer to the $1.25/day line.

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 per cent. 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 per cent and the $2.50 poverty rate as 85.7 per cent (see Chen and Ravallion, 2010).

Evidently then, if one uses NA rather than survey means, it is necessary to consider carefully how to adjust the poverty line(s) to allow for the systematic differences between the two means. One of the few examples that do make such an adjustment is Hillebrand (2008), who used NA data and projections from the International Futures Model[20] to forecast global poverty in 2015 and 2050. Hillebrand's method for developing a global distribution uses Bhalla's (2002) simple accounting procedure, whereby the national income distribution (quintile and decile) data are 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.[21]

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. To make allowance for the use of NA rather than survey means, when estimating poverty headcounts he 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 $1/day poverty line (which was in fact $1.08/day in 1993 PPP $) (Hillebrand, 2008: 729). In effect he is indicating that when one calculates distributions using NA consumption means, rather than survey means, it is necessary to inflate the $1/day poverty line by a factor of 1.4 to produce an 'equivalent' poverty line for use with NA means —we discuss later how we use GrIP to derive the equivalent adjustments for this and other poverty lines.

Hillebrand also attempts to estimate the effect of differing assumptions concerning the impact of future growth on national income distributions. As previously noted, forecasting future changes in national distributions is extremely contentious, so it is common to base forecasts on the simple assumption of static national distributions (i.e. that future within-country distributions remain the same as the most recent surveyed distribution). In addition to this static-distribution assumption, Hillebrand also 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.[22]

Hillebrand (2008) forecasts that under the high-growth scenario with static inequality the number of people in extreme poverty ($1/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 people in 2015 but then rise above current levels to 1.237 billion in 2050. These findings indicate that poverty forecasts are particularly sensitive to variations in growth forecasts and to different assumptions about future inequality changes.

2.5 OTHER FORECASTS

One further 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 using the Povcal dataset, survey means and semi-elasticities to incorporate changes in inequality. The growth scenarios seek to show maximum–minimum 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 people will live in MICs, and that this will largely be accounted for by poverty in India and Nigeria.

Dercon and Lea's use of semi-elasticities is, however, not unproblematic. They argue that semi-elasticities mean that the impact of changes in distribution are implicitly included in their forecasts. However, as Lenagala and Ram (2010) show, semi-elasticities —the elasticity of poverty with respect to real GDP per capita or the ratio of the fall in the poverty rate to the percentage increase in real GDP per capita —are not stable over time and are sensitive to different poverty lines even within the same country: Lenagala and Ram (2010) note that: first, the elasticities generally decline over time —the poverty-reducing impact of income growth weakens over time; second, 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-elasticityhas little logical correspondence to what actually happens as income growth shifts the national distribution curve. For this reason we consider that semi-elasticities are —if at all —only suitable for short-term poverty forecasts.

One final caveat to apply to all these estimates, including our own here, is that long-overdue revisions to national accounts, such as those recently in Ghana and imminently in Nigeria, will lead to some drastic revisions in the source data for all these estimates and are certain to have an impact on any estimates for world poverty, especially where they relate to large, populous countries (for greater detail, see Jerven, 2013).

3 THE GRIP (GROWTH, INEQUALITY AND POVERTY) MODEL

3.1 THE MODEL

In this paper we introduce a set of forecasts for global poverty derived using 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 user to combine survey distributions with either survey or NA means. Survey distributions (quintile and upper and lower decile data) are taken (in this order of preference) from PovcalNet, World Development Indicators or the UNU WIID V2.0c (May 2008) database.[23] 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 many more countries than, say, the Povcal countries which are used by the World Bank to estimate global poverty and which are predominantly LICs and MICs.[24]

Even though these datasets have greatly improved their global coverage in recent years, there are still some significant gaps in the data so that, 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. In years subsequent to the most recent survey the distribution is generally assumed to remain unchanged from that survey (static inequality assumption —see later for how this is modified in the dynamic inequality analyses). However, 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 user to choose to estimate —or 'fill' —a country's missing distributions with the (not 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 are available). Such an approach is used by Chen and Ravallion (2010) but only based on regional averages, not on income categories. Chandy and Gertz (2011) noted that they do not 'fill' the gaps (because they focus on recent years where data coverage is already high).

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, 2012), the GrIP model uses a linear interpolation method (described in more detail in Edward, 2006) that ensures that sub-quintile disaggregations 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.

As noted above, the GrIP model enables the user to decide whether to use **survey** (Option 1 in the model) or **NA means** (Option 2 in the model). When using survey means (Option 1), for countries where there are 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.

The model also allows the user to choose which NA measure to use as the source of the NA means. Typically the most suitable means to use are GDP per capita or HFC per capita. In this paper all the figures are based on HFC means (in 2005 PPP $). Because coverage of GDP data is generally better than that of HFC data, where GDP data exist but HFC data do 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 5 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 of inequality 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.

TABLE 5

Coverage (cov.) 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. (%)	Consumption cov. (%)	No. of countries	Pop'n cov. (%)	Consumption cov. (%)	No. of countries	Pop'n cov. (%)	Consumption 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.

To produce growth scenarios we use somewhat similar assumptions to those in Karver et al. (2012) and Sumner (2012a) but derive the forecast rates from more recent IMF WEO figures. This means that the estimates are based on the average growth rate from 2010–2017 (rather than 2009–2016 used by Karver and Sumner). We, therefore, use the following three scenarios for GDP PPP growth estimates as the forecast growth rate for 2010–2040:[25]

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

In our forecasts some other adjustments were also made to remove some anomalies.[26] 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.[27]

Initially we present results to 2040 for each of the three scenarios calculated on the assumption of static distribution (i.e. that the distribution in forecast years is the same as the most recent available survey for each country). However, we do also 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, rural–urban[28] weighting and NA/S ratios). The main purpose of this dynamic analysis is to investigate whether the assumption of static distribution, as used both in some of our forecasts and in many of the forecasts produced by others and described earlier in this paper, introduces a significant error 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 has increased in recent years in some countries, 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).[29]

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 needs to be made to adjust the poverty lines derived by survey means used by the World Bank 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/day) when applied to Option 1 (S). The adjusted poverty lines used in Option 2 are $1.74, $2.88 and $15.30/day (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.

3.2 HISTORICAL POVERTY ESTIMATES

The combination of different modelling assumptions with a casual approach to the applicability of poverty lines can generate, but also obscure, some surprising analyses of historical poverty.[30] We, therefore, consider it important that, before a model is used to forecast future poverty, some attempt is made to validate the model's reliability as an estimator of historical poverty levels (not only in terms of absolute values in a single year but also, and importantly for having confidence in any forecasts, in trends over several years). Only once one is satisfied that a model provides reasonable historical estimates of poverty can one then progress to having any faith in forecasts derived from it. If this is not the case, then before any assertions can be made about a new model identifying different insights into future poverty levels, it becomes necessary first to justify the presence of any historical differences.

Since the World Bank's '$1/day' definition of extreme poverty is widely recognised, we have chosen to compare the GrIP model against recent World Bank estimates of historical poverty levels. These estimates, which are based on available surveys and the new ICP data on PPP exchange rates, are available from PovcalNet and in related publications. As we show here, the GrIP model accords well with historical poverty estimates from the World Bank.

TABLE 6

Comparison of GrIP and World Bank Estimates of Numbers of People Living below $1.25/day and $2/day

	1990		1996		2002		2008	
Region	**WB**	**GrIP**	**WB**	**GrIP**	**WB**	**GrIP**	**WB**	**GrIP**
$1.25/day								
East Asia and Pacific	926	937	640	646	523	522	284	284
Europe and Central Asia	9	3	18	29	11	16	2	11
Latin America and Caribbean	53	51	54	53	63	63	37	36
Middle East and North Africa	13	19	12	21	12	7	9	9
South Asia Region	617	596	631	609	640	624	571	539
Sub-Saharan Africa	290	326	349	368	390	406	386	397
China	683	693	443	444	363	360	173	168
East Asia less China	190	244	180	202	144	163	111	116
India	436	422	442	435	461	466		411
South Asia less India	144	174	153	174	155	157		128
Total	**1909**	**1932**	**1704**	**1727**	**1639**	**1638**	**1289**	**1275**
$2/day								
East Asia and Pacific	1334	1267	1140	1149	984	979	659	657
Europe and Central Asia	32	18	53	73	37	52	10	27
Latin America and Caribbean	98	95	102	102	118	116	71	72
Middle East and North Africa	53	61	57	73	57	47	44	45
South Asia Region	959	954	1047	1049	1120	1135	1125	1115
Sub-Saharan Africa	389	398	466	478	533	542	562	567
China	961	925	792	813	655	657	395	394
East Asia less China	313	342	316	337	299	323	264	263
India	702	720	757	786	813	856		848
South Asia less India	224	234	252	263	271	279		267
Total	**2864**	**2794**	**2865**	**2924**	**2849**	**2873**	**2472**	**2483**

Sources: GrIP calculation for HFC and Option 1 adjusted for shortfalls in coverage by region. World Bank data from PovcalNet (downloaded 19 October 2012) with additional data for India and China from Chen and Ravallion (2012).

Recent World Bank estimates (Chen and Ravallion, 2012) are available for poverty in 2008 (and for every three years prior to then, going back to the early 1980s). Six yearly comparisons with the GrIP model, using survey means (i.e. Option 1) since 1984 are given in Table 6 (numbers show millions of people below the $1.25/day and $2/day poverty lines).[31] In general, the GrIP estimates closely mirror the World Bank's. Given the scope for differences in assumptions (e.g. in adjusting for NA to survey differences and in compensation for shortfalls in coverage) the results look very reasonable. Overall this suggests that the GrIP model is aligned very well with World Bank approaches.

The alignment of GrIP with the World Bank approach offers an interesting comparison with Chandy and Gertz's analysis. They present figures for 2005 (historical estimates) and 2010 (forecast) poverty headcounts using their method of survey means and forecast growth rates for NA per capita private consumption. Not surprisingly, since they are historical estimates derived from PovcalNet, their global $1.25/day poverty headcounts in 2005 align reasonably well with the World Bank figures. However, their model leads to significantly different estimates when they forecast poverty in 2010 (as compared, say, to the World Bank's historical estimates for 2008). More data are available since Chandy and Gertz's forecast was produced, so that by using GrIP with survey means (Option 1), which as is shown above closely replicates the World Bank results, we can calculate a historical estimate for 2010 to explore the differences here. Table 7 illustrates these figures.

TABLE 7

Comparison of Trends in Poverty Headcounts (millions) between World Bank, GrIP and Chandy and Gertz Models

	Headcounts (millions)			Reduction in headcount			
	2005			World Bank 2005–2008	GrIP 2005–2008	GrIP 2005–2010	Chandy and Gertz 2005–2010
Region	**World Bank**	**GrIP**	**Chandy and Gertz**				
$1.25/day							
East Asia and Pacific	332	327	305	48	43	110	165
Europe and Central Asia	6	18	16	4	7	9	8
Latin America and Caribbean	48	54	45	11	17	16	10
Middle East and North Africa	10	10	9	1	1	-1	2
South Asia Region	598	559	583	27	20	53	265
Sub-Saharan Africa	395	415	380	9	19	-3	10
China	212	203		39	35	84	153
India	456	432		29	22	35	230
Total	1389	1383	1338	100	108	184	460

Sources: As for Table 6 plus Chandy and Gertz (2011).

While the poverty headcounts in 2005 from all three methods are broadly similar, inspection of the changes over time reveals striking differences. GrIP closely agrees with the World Bank figures for changes between 2005 and 2008. However, when GrIP is used to extend that period to match Chandy and Gertz's 2005–2010 period (World Bank figures for 2010 are not currently available), we see some striking differences with much faster reductions in poverty in Chandy and Gertz's forecasts than in GrIP's historical estimates, especially in India (230 million people rather than 35 million) and China (153 million rather than 84 million).

Presumably, this sizeable difference arises largely as a result of forecasting assumptions (since the core source data on survey means, distributions etc. are the same, and all three models are reasonably in agreement when using historical data). Given the close alignment historically between GrIP and the World Bank's Povcal-derived figures we are inclined to see the difference, particularly in the case of India, as evidence that poverty forecasts are, not surprisingly, very sensitive to differences in model assumptions. In the case of Chandy and Gertz we highlighted above differences in the treatment of survey mean growth (notably that the World Bank discounts growth rates in India and China), adjustment of distributions and urban–rural population growth that might account for the divergence of estimates. At the very least, that forecasts can diverge so widely over even relatively short periods of time should caution us that it is important to develop forecasts under a variety not only of scenarios but also of modelling assumptions (as we do below when comparing, for example, static versus dynamic inequality forecasts) so that uncertainties and variability can be better appreciated before deciding policy on the basis of forecasts.

4 THE POSSIBLE FUTURE EVOLUTION OF GLOBAL POVERTY: STATIC VERSUS DYNAMIC INEQUALITY

4.1 BACKGROUND

In this section we take the GrIP v1.0 model and make global poverty projections based on static inequality and then on dynamic (changing over time) inequality. We present separate forecasts derived using survey means (Option 1), for optimum comparability to World Bank figures, and NA means (Option 2), using HFC means, for optimum comparability with the work of Kharas/Kharas-Rogerson/Hillebrand and others.

Initially, for each option we present optimistic, moderate and pessimistic economic growth forecasts and assume static distributions (i.e. we assume that in forecast years the national distribution of consumption is the same as for the most recently available survey). We have also classified the countries into forecast country income category (LIC, MIC and other categories) using forecast GNI figures (derived by applying GDP multipliers from 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 the World Bank thresholds for 2010 to determine country income category inflated at the appropriate rate for the relevant forecast.[32]

Table 8 shows estimates for forecast GDP per capita as percentage of 2010 GDP (for absolute figures, see also Annex Table A1). One aspect which is particularly striking is the doubling (pessimistic growth scenario) or possibly sevenfold increase (optimistic growth scenario) of income per capita in East Asia and the Pacific region, which sits side by side with sub-Saharan Africa's rise in per capita income, which could be in the order of a 150 per cent (optimistic) increase but could alternatively rise by as little as 10 per cent over 30 years. This points to the enormity of the range of possible income per capita outcomes over the next 30 years.

TABLE 8

Forecast GDP per capita as Percentage of 2010 GDP

	Pessimistic growth scenario				Optimistic growth scenario			
Region	**2020**	**2025**	**2030**	**2040**	**2020**	**2025**	**2030**	**2040**
East Asia and Pacific	125	143	167	234	171	235	329	684
Europe and Central Asia	106	111	116	128	121	135	152	198
Latin America and Caribbean	110	117	125	146	134	158	187	269
Middle East and North Africa	107	110	115	127	131	150	175	253
North America	105	108	112	121	120	132	146	181
South Asia Region	124	140	160	212	174	234	316	594
Sub-Saharan Africa	98	99	102	109	126	147	173	250
China	147	181	224	351	221	334	507	1193
East Asia less China	101	106	112	129	122	141	166	243
India	128	146	168	228	182	249	342	661
South Asia less India	110	117	125	148	140	169	207	323
Total	109	115	124	147	135	164	202	330

4.2 THE SCALE, LOCATION AND COST OF (ENDING) POVERTY IF INEQUALITY IS STATIC

Estimates and graphs for $1.25, $2 and $10 poverty are shown in Figures 1 (survey means) and 2 (NA means). Data tables for the same dataset are given in the Annex Tables A2 to A4.[33] The $1.25 poverty line is —of course —the well-known extreme poverty line. The $2 poverty line is often considered to be a more reasonable line, being close to the median poverty line of all developing countries (Chen and Ravallion, 2010; 2012). The $10 line is what one might call the 'security from poverty' line on the basis that vulnerability to poverty only drastically drops at levels well above the extreme poverty line. The $10 line has been identified by Pritchett (2006) and empirically explored in Chile, Mexico and Brazil by López-Calva and Ortiz-Juarez (2011).

A similar picture of declining rates of poverty reduction emerges for $2 poverty, which can be expected to fall under all scenarios. In the optimistic scenario $2 poverty could reduce rapidly to 2025 and more modestly thereafter, falling from around 2 billion people in 2010 to 600 to 700 million in 2040. In the pessimistic scenario falls will be much smaller, with the poverty headcount remaining as high as 1.5 billion in 2040. Figures 3 and 4 (which use 2010 income categorisations throughout) show that most of these reductions will be in countries that are currently non-fragile MICs (a grouping that includes and is dominated by India and China). Poverty in current LICs and fragile MICs will prove to be rather more intractable.

Surprisingly, $10 poverty has been increasing in recent decades, indicating that although the number of people in extreme poverty may have been falling, the number vulnerable to falling into poverty has been increasing. The optimistic growth scenario would forecast that $10 poverty will peak in the next few years at around 5 billion people. For some that may already be an alarmingly high 70 per cent of global population. However, under the pessimistic forecast $10 poverty is expected to keep on rising, perhaps peaking around 2030 or 2040 at close to 6 billion people.

FIGURE 1

Global Poverty Headcounts (millions): Option 1 (Survey Means); Static Inequality; Three Growth Scenarios (Pessimistic, Moderate and Optimistic)

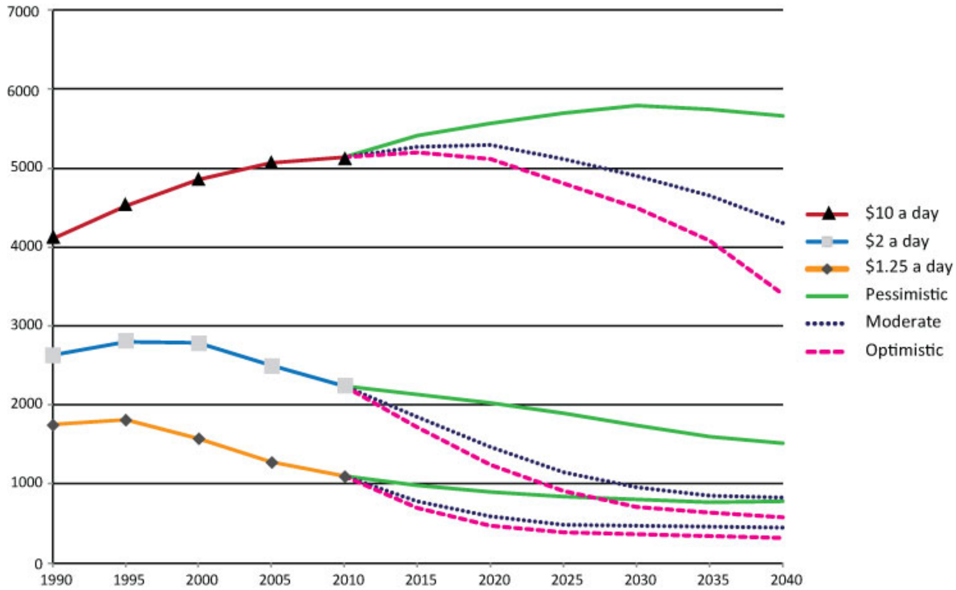


FIGURE 2

Global Poverty Headcounts (millions): Option 2 (NA Means); Static Inequality; Three Growth Scenarios (Pessimistic, Moderate and Optimistic)

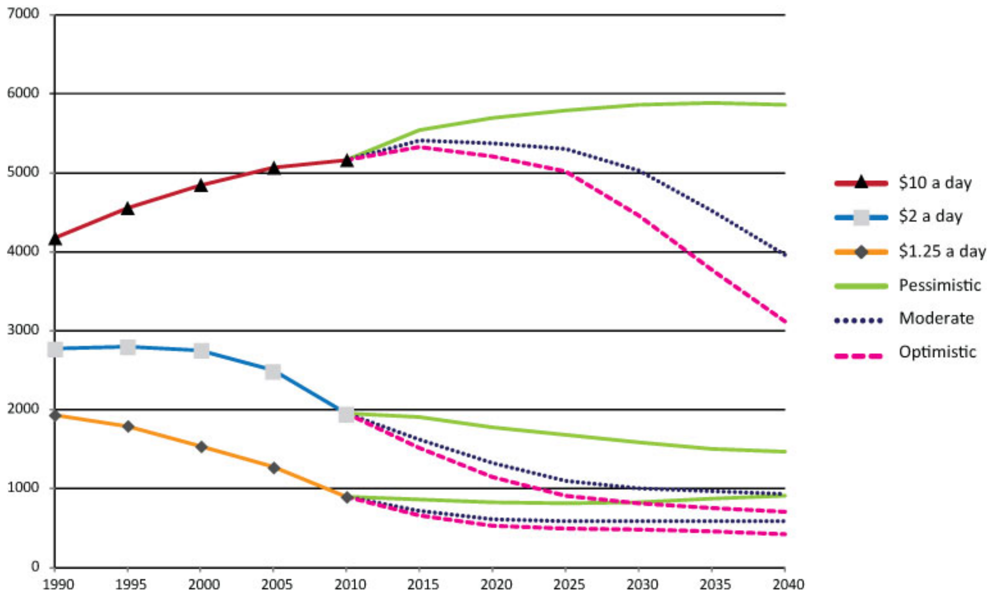


FIGURE 3

Poverty at $2, Headcounts (millions) in Fragile and Stable LICs and MICs by Current Income Categories: Option 1 (Survey Means); Static Inequality; Two Growth Scenarios (Pessimistic and Optimistic)

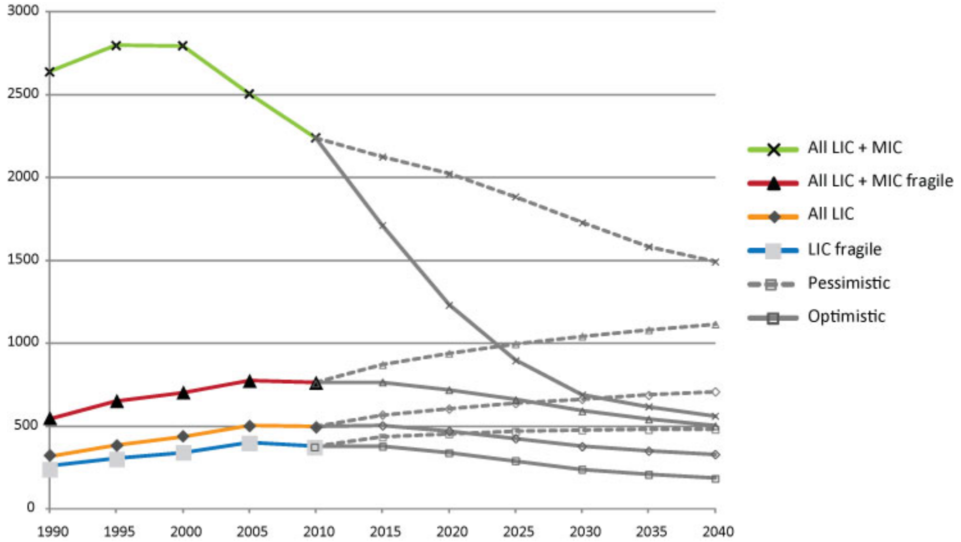
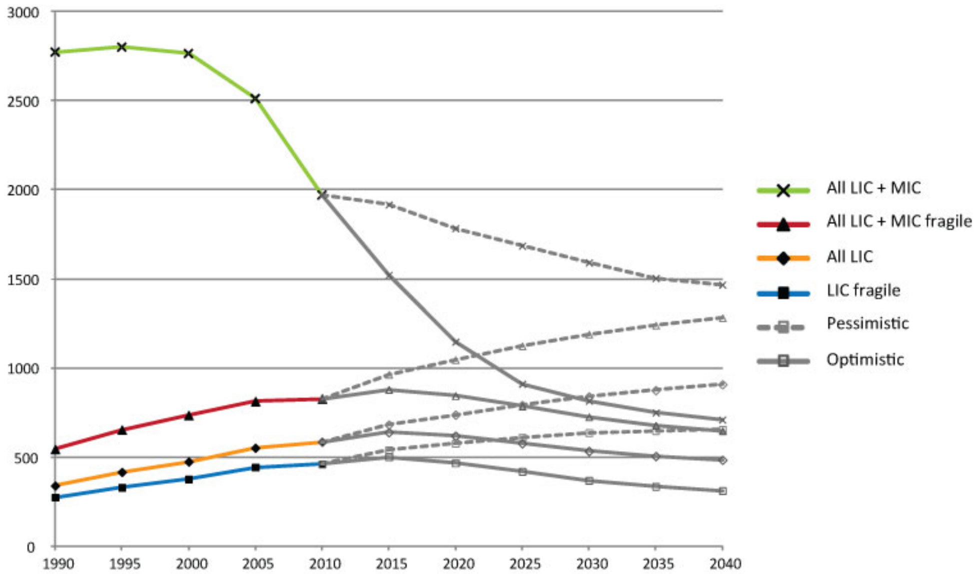


FIGURE 4

Poverty at $2, Headcounts (millions) in Fragile and Stable LICs and MICs by Current Income Categories: Option 2 (NA Means); Static Inequality; Two Growth Scenarios (Pessimistic and Optimistic)



Comparison of Figures 1 and 2 shows that as long as appropriate adjustments are made to poverty lines to allow for systematic differences between survey and NA means, then the total global poverty levels out to 2040 are broadly similar in both methods. Of course if these necessary adjustments are not made, then the use of NA means will lead to much lower headcounts for a given poverty line —for example, the $1.25 global poverty headcounts in 2010 would be more than 400 million lower if this adjustment were ignored, and for $2 poverty they would be more than 800 million lower. Most of the difference in these static forecasts, therefore, arises from differences in forecast growth rates (we discuss later how making dynamic projection of inequality changes further increases the range of differences between forecast outcomes). Poverty levels in the future are very dependent on future growth, so it is worth noting that while we consider the pessimistic forecast to be a reasonable lower-bound to global growth, at least one reviewer has suggested that even this scenario may still be too optimistic so that even the worst-case outcomes in these figures may be exceeded.

Although the use of survey means or NA means has only a modest impact on the global poverty headcounts, it has a significant impact on the geography (scale and location) of poverty. This is clearly brought into focus by comparing the three poverty lines. For $10 poverty there is remarkably little difference between the two approaches (Table 9), with, for example, China and India each accounting for one quarter of global poverty in both methods. As the poverty line is reduced, significant differences arise. With the $2 line India accounts for 38 per cent of global poverty when survey means are used but just 21 per cent 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. Balancing this out, 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.

TABLE 9

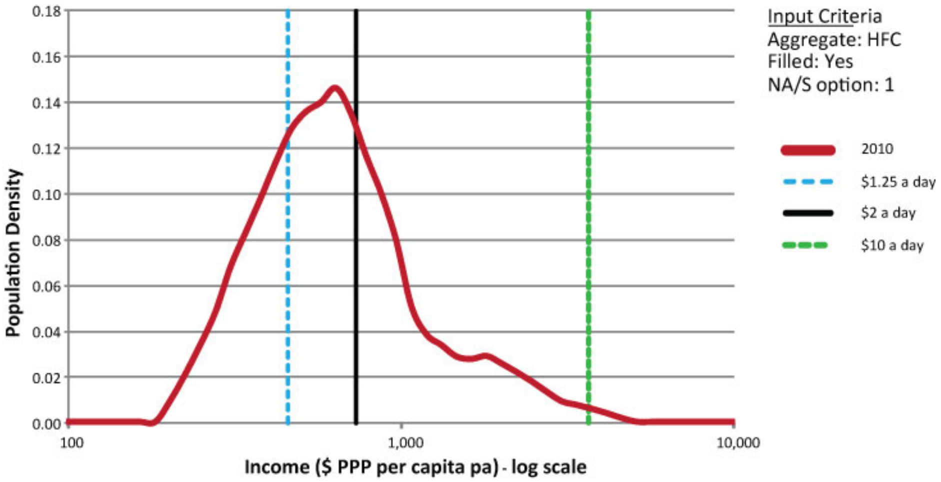
Proportion of Global Poverty by Region in 2010 (S = survey mean; NA = national accounts mean)

	$1.25		$2		$10	
Region	**S**	**NA**	**S**	**NA**	**S**	**NA**
East Asia and Pacific	18%	26%	22%	31%	34%	35%
Europe and Central Asia	1%	1%	1%	1%	6%	5%
Latin America and Caribbean	3%	4%	3%	4%	7%	8%
Middle East and North Africa	1%	2%	2%	2%	5%	5%
North America	0%	0%	0%	0%	1%	1%
South Asia Region	46%	18%	49%	32%	32%	31%
Sub-Saharan Africa	31%	49%	23%	30%	16%	16%
China	11%	22%	14%	24%	23%	25%
India	36%	9%	38%	21%	24%	23%
LICs	30%	47%	22%	30%	14%	14%
MICs	70%	53%	78%	70%	84%	84%
World	100%	100%	100%	100%	100%	100%

The poverty headcount in India is particularly sensitive both to this effect and to the different growth rates. This seems to be 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 people.

FIGURE 5

Population Distribution Curve for India



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

> "Because there are nearly 200 million Indians who live between $1.00 and $1.25 a day, the increase in the line adds many more Indians to the counts than it adds Africans. Although the prevalence of poverty remains higher in sub-Saharan Africa, the relative 'Indianization' of poverty…"

The choice of mean also has consequences for the question of how poverty is, and will be, divided between LICs and MICs. For example, survey means locate two thirds of $1.25 poverty in MICs in 2010, whereas NA means estimate 47 per cent in LICs and 53 per cent in MICs.[34] Evidently, the choice of whether to use survey or NA means generates significantly different geographies of global poverty, and these differences are greater the lower the poverty line. In general, at both the $1.25 and $2 lines and across most of the forecast scenarios, survey means increase the MIC poverty count, while NA means increase the LIC count —so the choice of means is important at that level.

Despite these issues, some broad trends can be discerned. Looking at extreme ($1.25) poverty there was in 2010 a roughly 30/70 (S) or 50/50 (NA) split between LICs and MICs. Under all scenarios this is likely to move so that, based on forecast income categories, LICs come to account for the larger share of extreme poverty. By 2030 it is estimated that the $1.25 split will be in the region of 60/40 or 70/30 between LICs and MICs. There is also some sign that by 2040 under the optimistic growth scenario this could reverse to 30/70 between LICs and MICs. However, from a policy setting perspective this reversal is probably not very relevant, because under the pessimistic scenario the split would still be in the region of two thirds in LICs and one third in MICs. The main cause of the difference seems to be that a number of current LICs might graduate under the optimistic scenario to MIC status between 2030 and 2040. If the split is calculated using current income status, then it remains two thirds in LICs and one third in MICs.

Looking at the $2 poverty line, in 2010 the split was 20/80 (S) or 30/70 (NA) between LICs and MICs. By 2030 and using forecast income categories this is likely to be a more evenly balanced 40/60 to 60/40 split between LICs and MICs. In other words, $2 poverty is likely to be roughly equally divided between LICs and MICs in the future —a finding which also applies if current income categories are used.[35]

Overall this finding supports a case for not removing aid from countries when they graduate from LIC to MIC status, and that any decisions to remove aid would need to be taken on an individual basis rather than by applying a universal criterion based on income category. Or, if a more generally applicable criterion is to be applied, then it might make sense to consider a wider range or different set of issues than merely whether, as is the case in the country income categorisations, a country has passed an arbitrary income per capita threshold. One alternative would be to consider the relative ability of countries to end poverty based on the total poverty gap and potentially taxable populations (see Ravallion, 2009).

This finding is also supported by the observation that while sub-Saharan Africa currently accounts for between 30 per cent (S) and 50 per cent (NA) of global extreme poverty, and around 25–30 per cent of $2 poverty, it is likely that in future poverty will become a predominantly African issue. By 2030 sub-Saharan Africa may well account for over 80 per cent of all extreme poverty, with absolute numbers of poor people either falling rather slowly (optimistic scenario) or rising quite significantly (pessimistic scenario). Elsewhere, extreme poverty in the Middle East and North Africa is estimated to increase even under the optimistic scenario. In Latin America it is forecast to remain fairly constant under the pessimistic scenario and fall only rather slowly under the optimistic scenario. The other area of note is that in South Asia (other than India) extreme poverty may persist in 2040 under the pessimistic scenario but could be largely eradicated under the optimistic scenario. Forecasts for $2 poverty follow a broadly similar pattern but with slightly less concentration on sub-Saharan Africa as a result mainly of the presence of not insignificant numbers in South Asia living between the $1.25 and $2 poverty lines.

It is useful also to note that a small number of countries dominate the poverty counts so that one could question whether it might simply be better to focus on the 20 developing countries that are currently home to 80 per cent of world poverty or the 30 countries that account for 90 per cent of world poverty in 2010. Similarly, when considering other categories of countries it may be best to focus on the smaller set of countries that dominate the poverty headcounts. For example, five MICs (Pakistan, Nigeria, Indonesia, China and India) currently account for 80 per cent of $2 poverty in MICs (82 per cent by survey means; 77 per cent by NA means), and just six fragile states account for two thirds of $2 poverty in all 45 fragile states (DRC, Nigeria, Pakistan, Kenya, Bangladesh and Ethiopia account for 65 per cent of poverty in fragile states in 2010 by survey means or 60 per cent by NA means).

Finally, looking at total poverty gaps (the gap between the aggregate consumption of poor people and the consumption required if they were all to be at the poverty line), the cost of ending $2 poverty has been falling and is forecast to continue to fall as a percentage of global GDP (Figure 6). In absolute dollar value (Figure 7) it is also expected to fall or, in the case of the pessimistic scenario and NA means, to stay effectively constant. Choices over use of survey or NA means national accounts are again significant. The current cost of ending $2 world poverty is somewhere between 0.9 per cent (S) and 1.2 per cent (NA) of global GDP. Interestingly, in 2015 the cost of ending $2 world poverty as a percentage of global GDP passes somewhere around the iconic 0.7 per cent figure of Official Development Assistance (ODA) commitments to poor countries (based on survey means; use of NA means with the poverty line adjusted as described earlier would place it nearer to 1 per cent). For interest only, Figures 6 and 7 also include data derived by applying the $2 poverty line without adjustment to the NA mean analysis, illustrating how failure to adjust the poverty line leads to significantly lower estimates of the scale and challenge of ending global poverty.

FIGURE 6

Total Poverty Gap (as Percentage of Global GDP), $2 Poverty Line by Survey Means (Option 1) and NA Means (Option 2); Static Inequality; Three Growth Scenarios (Pessimistic, Moderate and Optimistic)

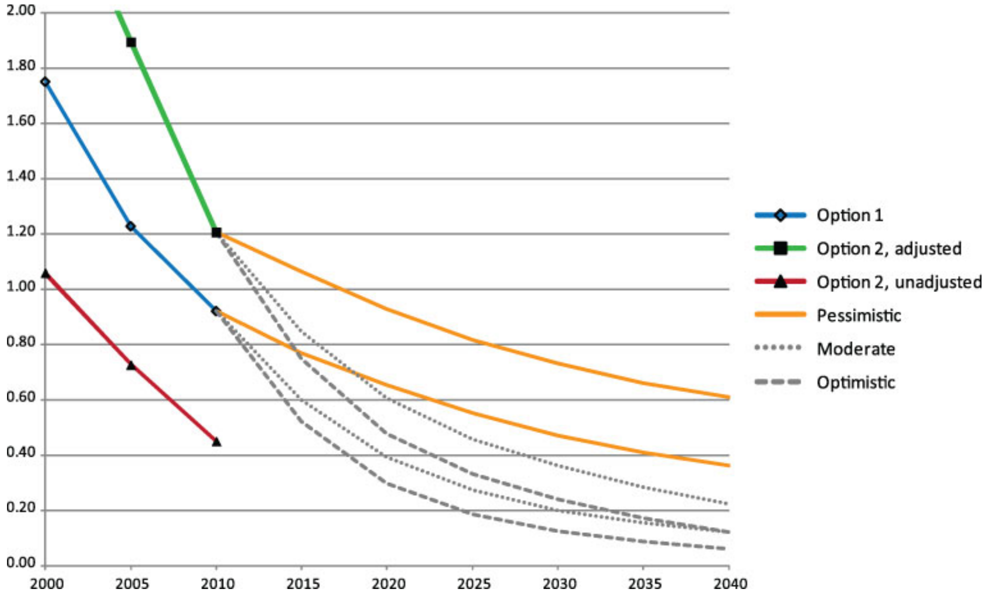
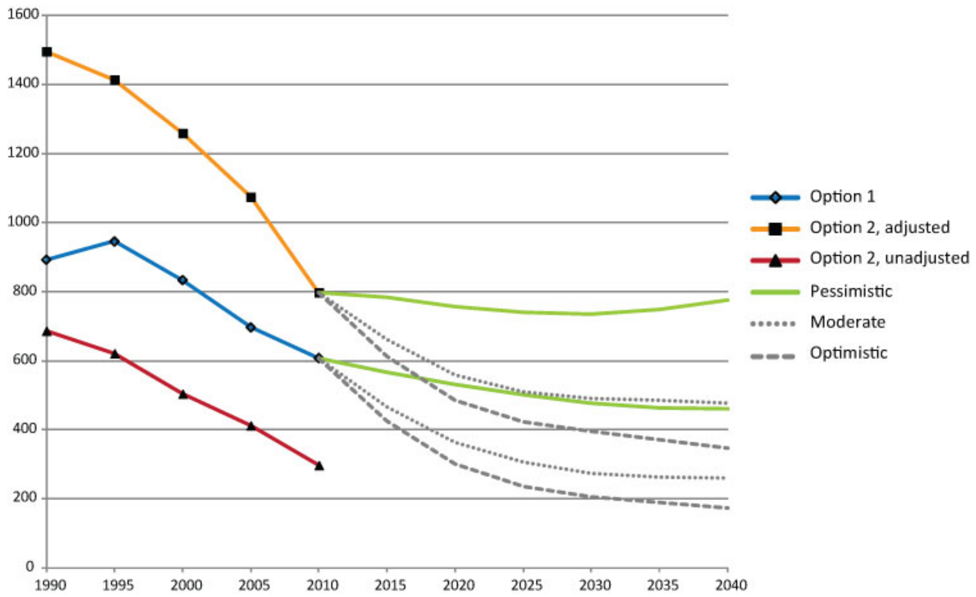


FIGURE 7

Total Pverty Gap ($bn 2005 PPP), $2 Poverty Line by Survey Means (Option 1) and NA Means (Option 2); Static Inequality; Three Growth Scenarios (Pessimistic, Moderate and Optimistic)



4.3 THE SCALE, LOCATION AND COST OF (ENDING) POVERTY IF INEQUALITY IS DYNAMIC

All of the above results are based on static inequality. As we noted above, the primary reason that most projections make the assumption of static inequality is because given the quality and variability of the survey data (both between and within countries over time) any forecasts of changes to distributions quickly risk being highly speculative. For this reason the estimates below should be treated cautiously and merely as indications of the impact that dynamic inequality changes might have on poverty estimates and forecasts.

We use three inequality scenarios to illustrate the impact of different inequality assumptions:

a) 'static inequality' = growth scenarios with static inequality, as per estimates in previous section;

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 Povcal 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; 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. Results of the analysis are shown in Figures 8 and 9 for \$1.25 and \$2 poverty with survey means. Figures 10 and 11 give results derived from NA means (for underlying data, see Annex Tables A5 to A7).

FIGURE 8

\$1.25 Headcount (millions), by Pessimistic/Optimistic Growth and Three Distribution Scenarios, Survey Means, 1990–2030

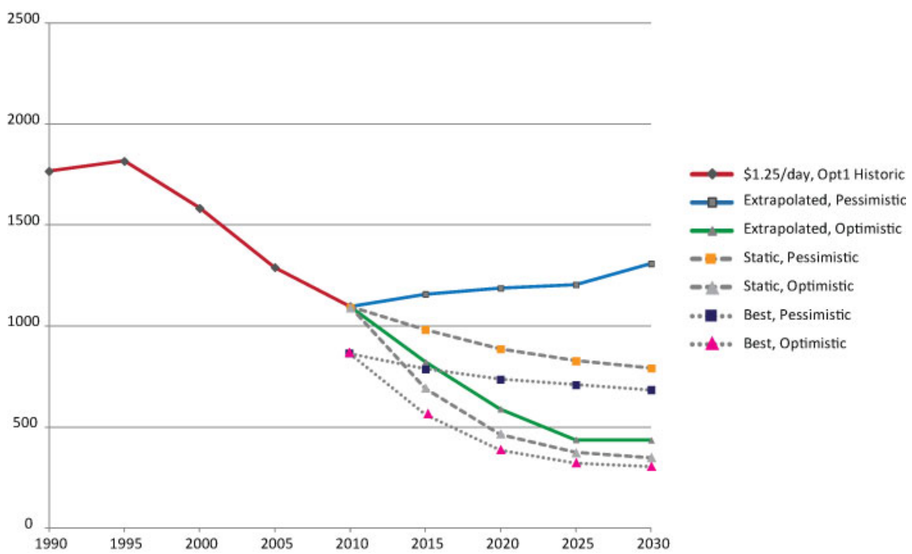


FIGURE 9

$2 Headcount (millions), by Pessimistic/Optimistic Growth and Three Distribution Scenarios, Survey Means, 1990–2030

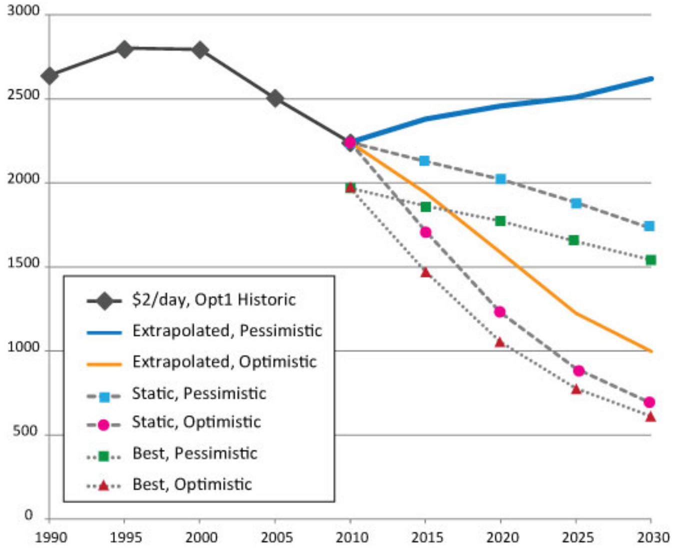
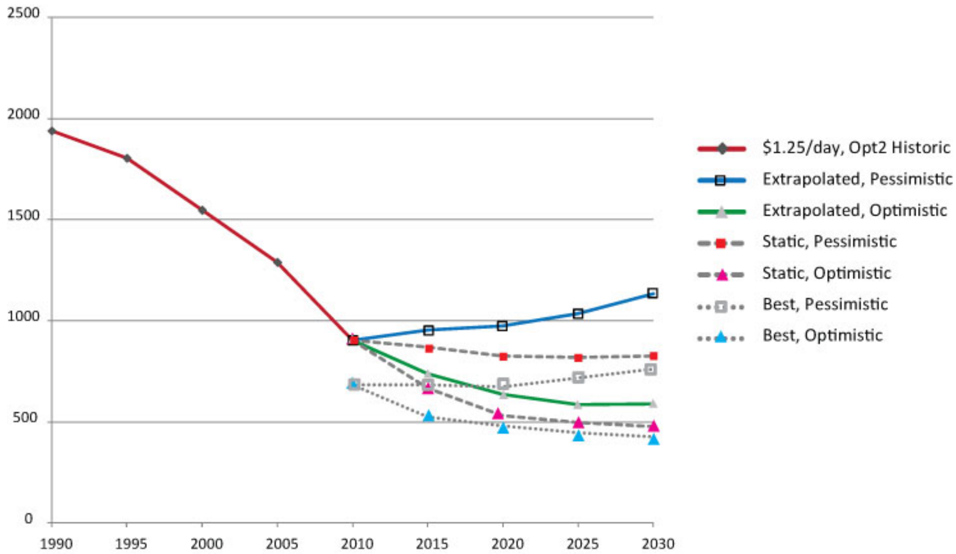


FIGURE 10

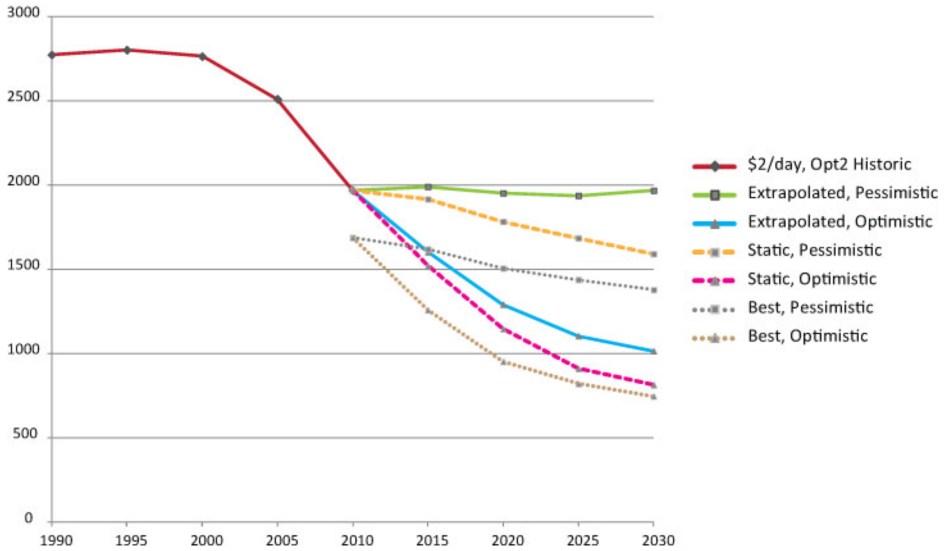
$1.25 Headcount (millions), by Pessimistic/Optimistic Growth and Three Distribution Scenarios, NA Means, 1990–2030



Notes: Survey means; optimistic/pessimistic = growth at IMF WEO/Half IMF WEO; extrapolated/static/best = current inequality trends/static inequality/'best-ever' distribution.

FIGURE 11

$2 Headcount (millions), by Pessimistic/Optimistic Growth and Three Distribution Scenarios, NA Means, 1990–2030



Notes: Survey means; optimistic/pessimistic = growth at IMF WEO/Half IMF WEO; extrapolated/static/best = current inequality trends/static inequality/'best-ever' distribution.

4.3.1 The scale of global poverty

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 1 billion people to levels close to 300 million (3–4 per cent of the world's population) by 2030. However, this would require economic growth at 'optimistic' levels and changes in inequality towards each country's historic 'best ever' distribution. If optimistic growth occurs with just static inequality, then these falls would be reduced by around 50 million people. If current trends in inequality (the dynamic inequality situation) were to continue, then the falls would be reduced by about a further 100 million people.

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

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 400 million people in 2030, while the worst-case figure is 1.1 billion.

The $1.25 line is a low poverty line, and 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 2 billion to 600 million people by 2030 —if every country returned to its 'best ever' inequality. However, $2 poverty could also increase from current levels to exceed 2.5 billion people 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. Forecasts of global poverty in 2025 and beyond are sensitive to assumptions about inequality. The difference between poverty estimated on current inequality trends versus a hypothetical return to 'best ever' inequality for every country could be an extra 400 million $2 poor people 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 $2 poor people in 2030 in one scenario we estimate.

4.3.2 The location of global poverty

In this section we discuss projections by various country categories across 12 scenarios for growth and inequality (i.e. S or NA means; 'best ever', static or extrapolated dynamic inequality; optimistic or pessimistic growth). We have already noted that income categorisations (LIC, MIC etc.) may have limited use as ways to identify countries where aid might be directed in future. Kharas and Rogerson have also suggested that in future $2 poverty will be focused in "selected low-income and fragile countries" (2012: 5).

As noted earlier, we find that the use of NA consumption means, as per Kharas and Rogerson, generally has a bias of increasing the proportion of global poverty likely to be found in fragile states and LICs in contrast to the use of survey means as used by the World Bank. However, even using NA means, we cannot forsee that the bulk of remaining world poverty in 2025 will be in low-income fragile states. At most, we estimate that 50 per cent of global $2 poverty might be in fragile LICs in 2025, but the figure is more likely to be 30–40 per cent. If all (i.e. LIC plus MIC) fragile states are included, this rises to 70 per cent under one scenario, although a figure of 40–60 per cent might be more likely —still an increase on the current 35 per cent (see Annex Table A8).

It is worth noting, however, that the Kharas and Rogerson figure is derived using an unadjusted poverty line. Allowing for the adjustment cited earlier (a factor of 1.45 at the $2 poverty line), the equivalent poverty line in our analysis would be $1.40/day ($2 ÷ 1.45). This places the Kharas and Rogerson $2 line actually just slightly above the $1.25 line in our analysis. When we look at figures for the $1.25 line (Annex Table A9), we find this does not much alter our conclusions, namely that low-income fragile states are unlikely to account for much more than 50 per cent and all fragile states are unlikely to account for more than 70 per cent of global poverty in any scenario. Use of survey means would reduce all these figures by some 10 percentage points or more (i.e. 50 per cent figures above generally become 40 per cent or less etc.).

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 fragile (irrespective of Income Category) it seems premature to argue that aid should be refocused predominantly onto low-income and fragile countries. Instead, 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 classifications. To support this aim, we present in Figures 12 to 15 various estimates of the distribution of global ($2) poverty to 2030 against various country aggregations. These aggregations include: by region (Figure 12); by current and forecast income group (Figure 13); by 'fragile' status (Figure 14); and by developmental status (Figure 15). In these graphs 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 (see Annex Tables A5 to A7 for 2030 data for each scenario for \$1.25, \$2 and \$10 poverty lines).

These graphs illustrate the current and forecast uncertainty over the numbers of poor people. It is worth noting that the lines for 2010 are derived from just two numbers (the survey and NA means results). The maximum–minimum range of the 2010 lines is, therefore, simply the difference in current estimates of poverty resulting from whether one uses survey or NA means.

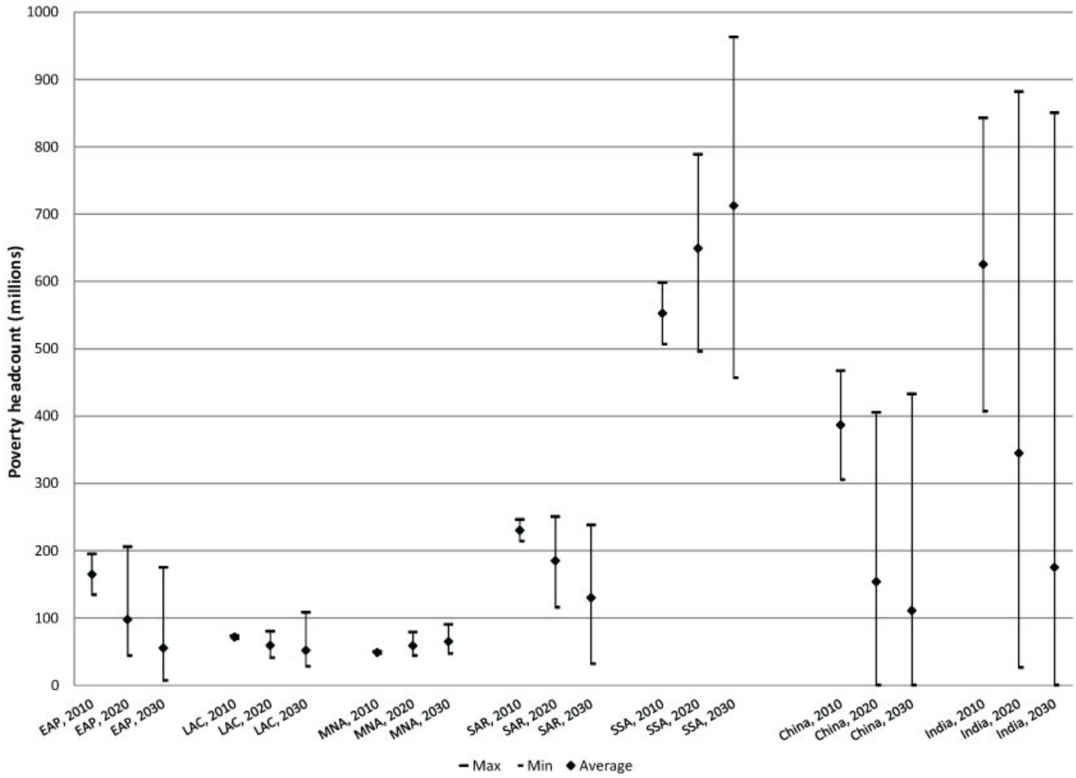
As previously noted, the use of NA means significantly alters the geography of poverty, with the greatest influence arising from very different estimates for poverty in India (Annex Table A12). Even when using just surveys (which are probably more reliable than the NA numbers in this case) there is still 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 'best-case' to 850 million people 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 poverty could range anywhere between zero and 850 million people, even if one just bases calculations on survey means. This range encompasses the range of possible poverty headcounts from NA mean calculations. In other words, notwithstanding that the choice of survey or NA means leads to significant uncertainty about **current** Indian poverty levels, the uncertainties about future levels would remain even if we limited our analysis just to the use of survey means.

Overall, Figures 12 to 15 reveal a highly uncertain and diverse range of possibilities for future poverty levels. We, therefore, suggest that these uncertainties need to be more clearly recognised and taken into account before policymakers decide to redirect or refocus aid budgets. There is a particularly large degree of uncertainty over poverty levels and forecasts for India, and to a lesser degree for 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. For this reason, in Figures 12 to 15 results for India and China are plotted **separately** and are **not** included in any of the aggregations.[36] This allows us to illustrate more clearly underlying trends across the smaller countries and is consistent with the notion that India and China are so large and unique that they should be treated as special cases when formulating aid policy.

Figure 12 shows that in 2010 global poverty at \$2 is largely focused in South Asia and India. This is particularly the case when using survey means, where South Asia alone accounts for 50 per cent of global poverty, while East Asia and sub-Saharan Africa account for 22 per cent each, and the rest of the world just over 5 per cent. By contrast, with NA means, just under 95 per cent 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 people. Elsewhere in the world poverty will most probably decrease.

FIGURE 12

Distribution of Global Poverty, $2 Poverty Line, to 2030 by Regions, by Survey Means (S) and NA Means, Pessimistic/Optimistic Growth and Three Inequality Scenarios



Note: Aggregations do not include China and India; 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. Aggregations do not include China and India.

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, then in 2030 Indian $2 poverty would still be around 450 million people. If that were 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 the poverty headcount in China may still be 150 to 200 million in 2030 (about 50 per cent of current levels) and may not even fall at all under the pessimistic scenario. It seems, therefore, from these figures, that poverty eradication in India is more dependent on economic growth, while in China it is more dependent on curbing rising inequality —although care needs to be taken here, 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.

Poverty in the rest of Asia 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 50 million, whereas optimistic growth might reduce current poverty levels (around 200 million people in 2010) by about 150 million people. 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.

In summary, therefore, in 2030 we can expect sub-Saharan Africa to dominate poverty headcounts. Poverty is likely to have reduced across Asia, probably very dramatically, but the actual extent of the reduction will depend on the amount of growth. Under the pessimistic growth scenario current poverty levels may be halved (roughly and assuming that lower economic growth comes with favourable changes in inequality), but under optimistic growth it could be largely eradicated (although this depends on China curbing rising inequality). In the rest of the world poverty will remain less than 10 per cent of the global total, but it is also likely to prove difficult to eradicate or reduce much.

Looking at the location of poverty by various country categorisations, we consider the location by country income groups (LIC and MIC, Figure 13), convergence groups (Figure 14) and fragile/stable countries (Figure 15). Recalling that in all these figures China and India have been separated out and excluded from the aggregations, Table 10 identifies their status against these categorisations.

TABLE 10

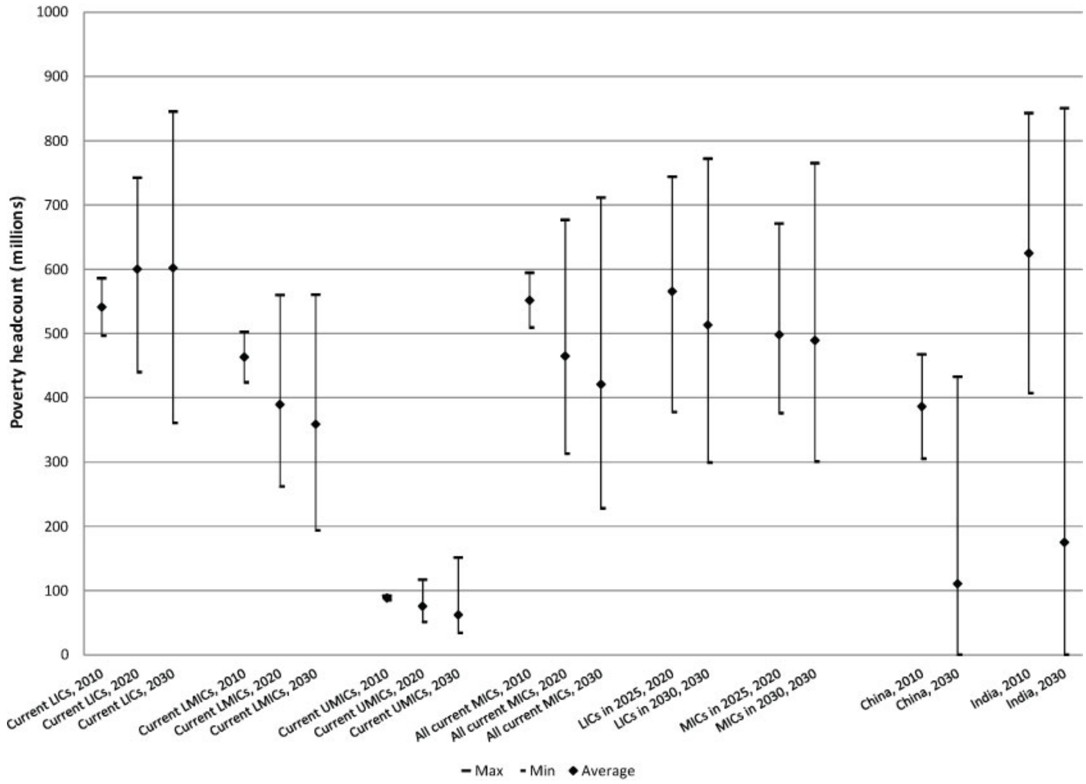
China and India Categorisation

	Income Category			Fragile		Converging	IMF Emerging Market	LDC
	2010	2020	2030 (Scenario)	OECD	World Bank			
China	UMIC	UMIC	HIC (Opt) UMIC (Pess)	No	No	Yes	Yes	No
India	LMIC	LMIC	UMIC (Opt) LMIC (Pess)	No	No	Yes	Yes	No

Figure 13 shows that in 2010 global poverty at $2 is largely focused in MICs. China, India and all other MICs account for 78 per cent (S) or 70 per cent (NA) of $2 poverty.[37] The general picture from this chart is that by 2030 poverty in LICs will probably have risen, while it is likely to have fallen in MICs (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) in 2030 using survey means there is, in all cases, more poverty in MICs than in LICs, with the greatest difference being in the pessimistic extrapolated scenario where MICs account for 29 per cent of global poverty and LICs for 23 per cent (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 per cent in LICs and 38 per cent in MICs. It, therefore, seems that even after removing India and China, which are both already MICs, there is no strongly compelling case here for ignoring poverty in MICs and focusing only on poverty in LICs —unless one wants to argue that the rising income of MICs means that their poverty can be left to concerns of domestic politics rather than international aid.

FIGURE 13

Distribution of Global $2 Poverty to 2030 by Income Groups, Survey Means (S) and NA Means, Pessimistic/Optimistic Growth and Three Inequality Scenarios



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

Figure 14 considers fragile states or 'fragile situations' using the OECD 'non-official' list of 45 such countries (see OECD, 2013a; 2013b) and World Bank 'Harmonised Lists of Fragile Situations' of 34 countries (see World Bank, 2013).

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: 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 —under certain definitions —not 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:[38]

> "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 (2009; World Bank, African Development Bank, Asian Development Bank) 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: 1).

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

Even if one assumes that fragile states in either list in 2010 will be fragile states in 2030 (which is a large assumption), we are still unable to foresee that the bulk of remaining world poverty in 2025 will be in low-income fragile states. Indeed, if current inequality trends continue, low-income fragile states may account for as little as a fifth of global poverty in 2025 or at most half —the range would again suggest caution in restructuring the aid industry on just one scenario. The average across the 12 scenarios is for 35 per cent of global poverty in fragile LICs (up from around 20 per cent in 2010), and, looking across the results, a figure of 25–40 per cent of global poverty being in fragile LICs seems most likely.

In every case the survey means produce lower proportions, and the NA means generate higher proportions of global poverty in fragile LICs. In short, the use of NA consumption means, as per Kharas and Rogerson, 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. Across the 12 scenarios the average for poverty in fragile MICs is 21 per cent of global poverty (up from around 12 per cent in 2010), and a range of 15–30 per cent seems likely.

There does not seem to be a case here, therefore, for distinguishing between middle- and low-income fragile states. 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 but being careful of which 'fragile states'. In this regard, the 34 countries in the World Bank's 'harmonised list of fragile situations' may be more useful, as in these states the poverty headcounts are forecast to rise under all scenarios. It may be, therefore, that the OECD fragile states list needs revisiting.

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:

> "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-incom e 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 this makes it quite difficult to be clear what group of countries are being referred to for certain. Further, one cannot determine exactly what Kharas and Rogerson mean by 'selected' countries. The 'top 10' countries listed in an annex (p. 32) account for 333 million $2 poor, but it is not clear what the other countries are that account for world poverty in 2025 outside these 10 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 A10 for $2 and A11 for $1.25), 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 per cent 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 100 milliom to 1.5 billion. **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 per cent of world poverty in 2025 (pessimistic growth, current inequality trends, survey means), but, on the other hand, that figure could be as low as 7 per cent (optimistic growth and best ever distributions, NA means). This again demonstrates 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 LICs 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.

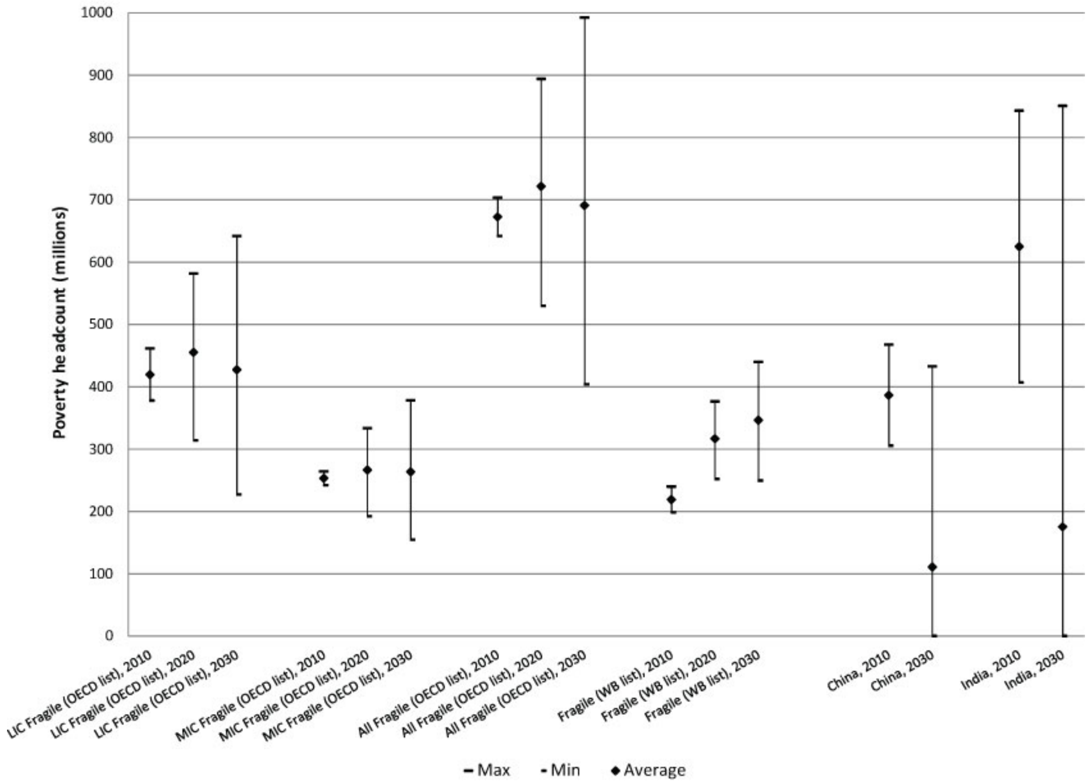
Third, if one uses the LICs that will be LICs in 2025 or the World Bank's fragile states lists, world poverty in 2025 drops significantly in the 'all LIC plus all fragile states' group across all estimates and, consequently, global poverty shifts back to stable MICs in all scenarios, meaning that the 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, to argue that the aid industry should be restructured around those same countries.

FIGURE 14

Proportion of Global Poverty in Fragile States, $2 Poverty Line, to 2030, Survey Means (S) and NA Means, Pessimistic/Optimistic Growth and Three Inequality Scenarios



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

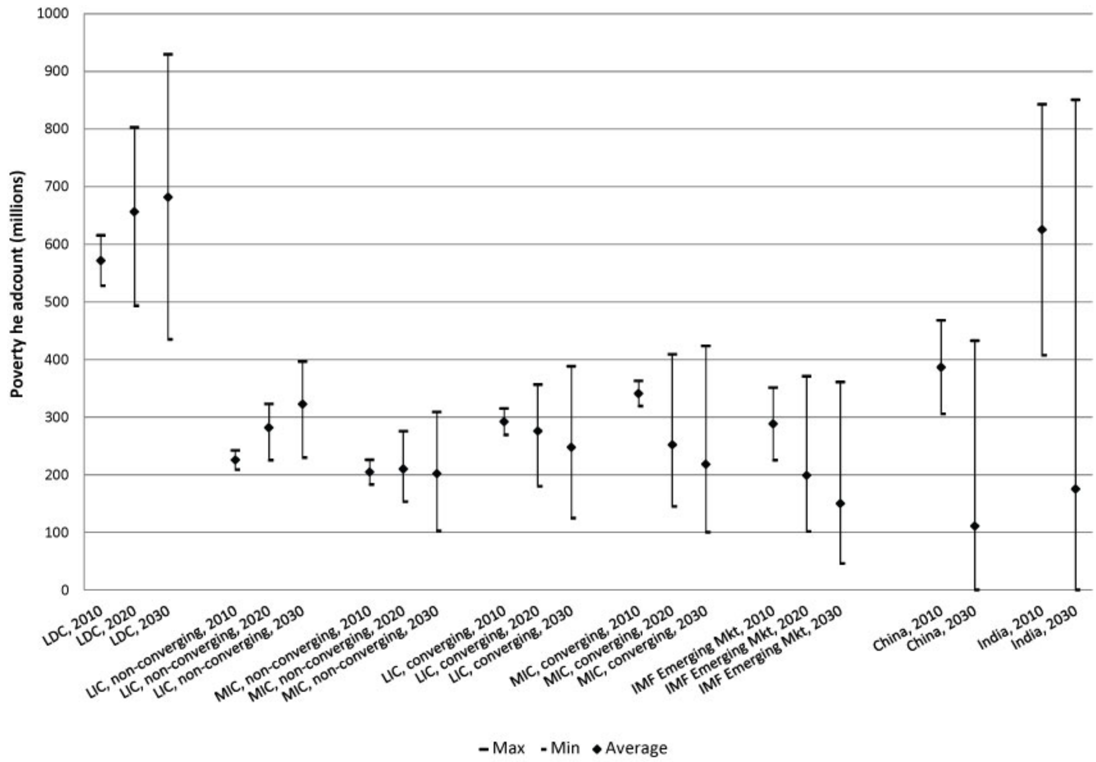
We have not made an exhaustive investigation of alternative prioritisation approaches (meaning what country categories might be useful to prioritise aid if aid is linked to poverty), but some possibilities are suggested in Figure 15, which shows the distribution of global poverty by 'country convergence groups'. We would argue that the categories of LIC and MIC (and fragile/non-fragile) are both constraining and arbitrary. The former categorisation has — at best —an unclear historical background (see Sumner, 2012b, for discussion). The latter typically conflates, via the practice of amalgamating different lists, conflict/post-conflict countries with countries with poor governance (see discussion in Hartggen and Klasen, 2010). An alternative is the OECD (2012: 35) '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 – high-income countries (HICs);
- converging – countries with GDP per capita growth more than twice the OECD HIC growth rate;
- struggling – countries with GDP per capita growth less than twice the OECD HIC growth rate and MIC at end of period; and
- poor – countries with GDP per capita growth less than twice the OECD HIC growth rate and LICs at end of period.

This produces a large list of more than 80 countries (63 have poverty data) that are 'convergers' in the 2000–2010 period (OECD, 2012: 256–8). Figure 15 also includes the UN Least Developed Country (LDC) group (48 countries) and a group that forms 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 in Figure 15).

FIGURE 15:

Distribution of Global $2 Poverty to 2030 by Convergence Groups, Survey Means (S) and NA Means, Pessimistic/Optimistic Growth and Three Inequality Scenarios



Note: as described in the text, aggregations do not include China and India. Sum of the convergence and non-convergence rows are 95–-99 per cent because there are 19 current LICs/MICs that do not appear in the OECD list of affluent, converging, struggling or poor countries.

For the LDCs, poverty headcounts are forecast to reduce (from about 500 million or 600 million in 2010) by at most 100 million by 2030. This would be under the optimistic growth scenario. If growth is closer to the pessimistic scenario, then poverty in LDCs is likely to rise, perhaps by as much as 250–300 million. The LDC categorisation may, therefore, still form a useful starting point for considering aid priorities.

Figure 15 also suggests that the 'four-speed world' list may be useful. It can be clearly seen that low-income non-converging (i.e. 'poor' or 'struggling') countries are likely to see their poverty headcounts increase by 2030. Middle-income non-converging countries will struggle to reduce poverty and could see their poverty headcounts rise. Low-income convergers are likely to see poverty headcounts fall, but it is not certain that they will do. Middle-income convergers currently account for more poverty than the low-income convergers, but it seems that they are rather more likely than LICs to see their headcounts fall by 2030. It appears, therefore, that, rather than refocusing aid on the basis of income category combined with fragile status, it might be more useful to look at the intersection of income category (or maybe income per capita) and convergence status.

4.3.3 The costs of ending global poverty

Finally, on the cost of ending poverty, the total cost of ending global $2 poverty in 2010 is estimated at US$600–800 billion (respectively, survey means and NA means) (2005 PPP$). This, it is estimated, would amount to 0.9–1.2 per cent of world GDP in 2010. If growth is strong but current inequality trends continue, this could fall to US$250–475 billion by 2030. This would amount to 0.2–1.0 per cent of estimated world GDP in 2030 under the same scenario. However, if growth is strong and countries return to their best ever distribution, the total poverty gap could fall further to US$175–350 billion in 2030 or 0.1–0.2 per cent of estimated world GDP in 2030 under the same scenario.

The difference between current inequality trends and a return to 'best ever' would be to reduce the cost of ending $2 poverty in 2030 (by taking the latter) by about US$300 billion on pessimistic growth trends and U$100 billion on optimistic growth trends.

In terms of the current cost of ending poverty (2010), it is estimated at US$100–200 billion for East Asia and the Pacific (survey versus NA means), US$175–275 billion for South Asia (NA means versus survey means) and US$190–360 billion for sub-Saharan Africa (survey versus NA means). Costs for India are estimated at US$100–200 billion, and for China US$70–175 billion. The current (2010) cost of ending $2 poverty in all fragile states (OECD 45 countries) is US$190–350 billion. For current MICs it is US$430–460 billion. The cost for the LDCs would be US$180–355 billion. The cost for IMF Emerging Market Economies is US$340–360 billion.

Annex Tables A13 to A15 provide estimates of the total poverty gap in 2025 and 2030 by each of the 12 scenarios used earlier.

5 CONCLUSIONS

A set of recent papers has sought to make poverty projections into the future about locations (or 'geography') of poverty. These have significant policy implications because it is only by understanding both the future scale and anticipated locations (or 'geography') 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 NA 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 that estimates of poverty levels in the future are very misleading.

In summary, 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 be very certain about 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. The likelihood is that poverty levels will fall in both countries, but it is hard to predict by how much.

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 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 fall much from those levels.

Looking to income classifications, currently most poverty is in MICs —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, contrary to proposals by, for example, Kharas and Rogerson, we find surprisingly little in the way of compelling evidence that aid should be refocused on low-income fragile states. 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 low-income fragile states —poverty reduction seems equally unlikely in the middle-income 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 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. Forecasts of global poverty in 2025 and beyond are sensitive to assumptions about inequality. The difference between $2 poverty estimated on current inequality trends versus a hypothetical return to 'best ever' inequality for every country could be an extra 1 billion poor people in 2030 in one scenario we estimate (pessimistic growth and survey means). Taking our scenario of optimistic economic growth, $2 poverty could fall to 800 million people by 2025 and 600 million people by 2030 if every country returned to 'best ever' inequality. However, if recent trends in inequality continue, those falls would be reduced by 500 million in 2025 and almost 400 million in 2030.

Where the world's poor people will be located is also dependent on changes in inequality to a certain extent, as well as on the methods used to estimate poverty. In 2025 and 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 India in particular —in global poverty. On the other hand, if inequality were to return to 'best ever' distributions for each country and growth were 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 2025 and 2030 and corresponding shifts away from South Asia.

Finally, the difference between current inequality trends and a return to 'best ever' would reduce the cost of ending $2 poverty in 2030 (by taking the latter) by about US$300 billion on pessimistic growth trends and U$100 billion on optimistic growth trends.

DATA ANNEX

TABLE A1

GDP Per Capita ($ PPP 2005)

		Pessimistic growth scenario				Optimistic growth scenario			
Region	**2010**	**2020**	**2025**	**2030**	**2040**	**2020**	**2025**	**2030**	**2040**
East Asia and Pacific	8770	10932	12576	14649	20553	14987	20583	28868	59980
Europe and Central Asia	20779	22106	22984	24041	26699	25227	28134	31687	41145
Latin America and Caribbean	10159	11204	11899	12721	14866	13656	16036	18992	27290
Middle East and North Africa	9169	9853	10114	10511	11669	11986	13720	16016	23169
North America	41480	43666	44974	46468	50262	49847	54947	60766	75022
South Asia Region	2782	3459	3904	4438	5885	4853	6497	8786	16520
Sub-Saharan Africa	2086	2040	2071	2121	2278	2636	3066	3611	5206
China	6851	10099	12415	15372	24074	15156	22875	34737	81726
East Asia less China	12114	12242	12822	13571	15599	14721	17071	20118	29390
India	3045	3892	4452	5121	6935	5557	7583	10423	20124
South Asia less India	1992	2189	2321	2489	2950	2791	3361	4116	6444
Total	9903	10756	11421	12253	14540	13411	16198	20015	32674

TABLE A2

Poverty Forecasts under Static Inequality, $1.25/day

$1.25/day	**2010**		**2015**				**2020**				**2030**				**2040**			
Static distributions			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
	S	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Headcounts (millions)																		
East Asia and Pacific	196	232	107	180	46	105	55	114	8	9	17	15	0	0	11	3	0	0
Europe & Ctrl Asia	9	12	7	10	5	7	6	8	3	4	3	5	0	0	1	2	0	0
LatAm & Caribbean	36	38	36	38	31	32	35	37	26	27	32	34	17	19	28	30	11	13
M East and N Africa	13	14	19	20	17	17	24	25	18	18	35	36	22	23	49	51	28	30
North America	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
South Asia Region	503	160	416	109	249	52	320	68	78	27	155	46	2	10	38	28	0	5
Sub-Saharan Africa	340	445	396	512	344	452	448	573	333	447	550	691	307	424	634	796	263	376
China	119	203	69	139	23	80	24	82	0	1	0	1	0	0	0	0	0	0
E Asia less China	77	30	38	41	23	25	31	32	8	8	17	14	0	0	11	3	0	0
India	398	79	315	35	179	0	226	2	42	0	84	0	0	0	0	0	0	0
S Asia less India	106	82	101	74	70	52	94	66	37	27	71	46	2	10	38	28	0	5
Total	**1097**	**902**	**982**	**869**	**691**	**665**	**887**	**825**	**465**	**531**	**793**	**827**	**348**	**477**	**761**	**910**	**302**	**424**
LIC (current)	324	426	388	518	268	384	388	518	268	384	428	574	229	345	466	630	184	299
LIC (current) and fragile	233	318	272	382	172	271	272	382	172	271	281	404	126	224	286	421	84	181
MIC (current)	773	476	498	307	197	146	498	307	197	146	365	253	119	132	295	280	118	125
MIC (current) and fragile	120	103	159	141	102	99	159	141	102	99	196	178	85	98	215	206	96	100
LIC (forecast)	324	426	368	486	256	368	400	526	255	368	438	584	218	291	473	621	95	107
MIC (forecast)	773	476	613	383	419	283	486	298	196	150	343	229	119	175	274	277	199	309
HIC (forecast)	0	0	0	0	16	15	1	0	14	12	12	14	11	11	14	12	8	9
Percentages of global total																		
East Asia and Pacific	18%	26%	11%	21%	7%	16%	6%	14%	2%	2%	2%	2%	0%	0%	1%	0%	0%	0%
Europe & Ctrl Asia	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	1%	0%	0%	0%	0%	0%	0%

LatAm & Caribbean	3%	4%	4%	4%	4%	5%	4%	4%	5%	5%	4%	4%	5%	4%	4%	3%	4%	3%
M East and N Africa	1%	2%	2%	2%	2%	3%	3%	3%	4%	3%	4%	4%	6%	5%	6%	6%	9%	7%
North America	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
South Asia Region	46%	18%	42%	13%	36%	8%	36%	8%	17%	5%	20%	6%	0%	2%	5%	3%	0%	1%
Sub-Saharan Africa	31%	49%	40%	59%	50%	68%	50%	69%	72%	84%	69%	84%	88%	89%	83%	88%	87%	89%
China	11%	22%	7%	16%	3%	12%	3%	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
E Asia less China	7%	3%	4%	5%	3%	4%	3%	4%	2%	1%	2%	2%	0%	0%	1%	0%	0%	0%
India	36%	9%	32%	4%	26%	0%	25%	0%	9%	0%	11%	0%	0%	0%	0%	0%	0%	0%
S Asia less India	10%	9%	10%	9%	10%	8%	11%	8%	8%	5%	9%	6%	0%	2%	5%	3%	0%	1%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
LIC (current) % total	30%	47%	40%	60%	39%	58%	44%	63%	58%	72%	54%	69%	66%	72%	61%	69%	61%	71%
MIC (current) % total	70%	53%	51%	35%	29%	22%	56%	37%	42%	28%	46%	31%	34%	28%	39%	31%	39%	29%
LIC (forecast) % total	30%	47%	38%	56%	37%	55%	45%	64%	55%	69%	55%	71%	63%	61%	62%	68%	31%	25%
MIC (forecast) % total	70%	53%	62%	44%	61%	43%	55%	36%	42%	28%	43%	28%	34%	37%	36%	30%	66%	73%
HIC (forecast) % total	0%	0%	0%	0%	2%	2%	0%	0%	3%	2%	2%	2%	3%	2%	2%	1%	3%	2%
Total Poverty Gap (TPG)																		
TPG ($bn 20005 PPP)	147	206	135	209	95	165	129	214	72	145	132	242	60	127	149	281	52	109
TPG as % global GDP	0.22	0.31	0.18	0.28	0.12	0.20	0.16	0.26	0.07	0.14	0.13	0.24	0.04	0.08	0.12	0.22	0.02	0.04

TABLE A3

Poverty Forecasts under Static Inequality, $2/day

$2/day	**2010**		**2015**				**2020**				**2030**				**2040**			
Static distributions			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
	S	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Headcounts (millions)																		
East Asia and Pacific	500	602	358	524	243	367	264	392	91	171	109	189	16	13	49	52	1	0
Europe & Ctrl Asia	26	29	23	26	17	21	20	24	10	14	13	18	2	5	7	11	0	0
LatAm & Caribbean	69	74	69	73	60	64	68	73	52	56	64	69	36	39	56	61	24	26
M East and N Africa	50	47	66	61	53	49	72	68	48	47	81	76	50	54	86	83	58	61
North America	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
South Asia Region	1089	621	1024	539	810	363	943	448	493	183	679	289	82	51	385	161	32	17
Sub-Saharan Africa	507	598	588	695	531	658	657	780	536	676	783	951	503	654	909	1100	447	606
China	305	467	222	365	147	252	150	257	38	109	35	105	0	0	0	2	0	0
E Asia less China	195	134	136	159	96	116	114	135	54	62	74	84	16	13	49	50	1	0
India	843	407	775	324	600	185	693	234	324	46	441	90	2	0	187	0	0	0
S Asia less India	246	214	249	214	210	178	250	215	170	137	238	200	80	51	198	161	32	17
Total	**2241**	**1971**	**2127**	**1918**	**1714**	**1523**	**2024**	**1785**	**1231**	**1148**	**1730**	**1592**	**689**	**816**	**1493**	**1468**	**562**	**711**
LIC (current)	497	586	605	738	470	620	605	738	470	620	664	840	378	534	709	908	330	485
LIC (current) and fragile	378	461	452	578	339	467	452	578	339	467	475	637	239	370	480	656	184	313
MIC (current)	1743	1384	1418	1045	761	528	1418	1045	761	528	1064	752	311	282	784	560	231	225
MIC (current) and fragile	264	242	333	309	249	225	333	309	249	225	378	350	213	191	406	374	171	163
LIC (forecast)	497	586	569	677	386	516	614	738	397	536	600	771	302	371	639	818	118	129
MIC (forecast)	1743	1384	1555	1238	1293	973	1407	1044	806	584	1105	793	355	417	825	620	418	557
HIC (forecast)	2	1	3	2	35	34	3	3	29	28	24	28	32	28	29	30	26	25
East Asia and Pacific	22%	31%	17%	27%	14%	24%	13%	22%	7%	15%	6%	12%	2%	2%	3%	4%	0%	0%
Europe & Ctrl Asia	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	1%	0%	1%	0%	0%

LatAm & Caribbean	3%	4%	3%	4%	4%	4%	3%	4%	4%	5%	4%	4%	5%	5%	4%	4%	4%	4%
M East and N Africa	2%	2%	3%	3%	3%	3%	4%	4%	4%	4%	5%	5%	7%	7%	6%	6%	10%	9%
North America	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
South Asia Region	49%	32%	48%	28%	47%	24%	47%	25%	40%	16%	39%	18%	12%	6%	26%	11%	6%	2%
Sub-Saharan Africa	23%	30%	28%	36%	31%	43%	32%	44%	44%	59%	45%	60%	73%	80%	61%	75%	79%	85%
China	14%	24%	10%	19%	9%	17%	7%	14%	3%	9%	2%	7%	0%	0%	0%	0%	0%	0%
E Asia less China	9%	7%	6%	8%	6%	8%	6%	8%	4%	5%	4%	5%	2%	2%	3%	3%	0%	0%
India	38%	21%	36%	17%	35%	12%	34%	13%	26%	4%	25%	6%	0%	0%	13%	0%	0%	0%
S Asia less India	11%	11%	12%	11%	12%	12%	12%	12%	14%	12%	14%	13%	12%	6%	13%	11%	6%	2%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
LIC (current) % total	22%	30%	28%	38%	27%	41%	30%	41%	38%	54%	38%	53%	55%	65%	47%	62%	59%	68%
MIC (current) % total	78%	70%	67%	55%	44%	35%	70%	59%	62%	46%	62%	47%	45%	35%	52%	38%	41%	32%
LIC (forecast) % total	22%	30%	27%	35%	23%	34%	30%	41%	32%	47%	35%	48%	44%	45%	43%	56%	21%	18%
MIC (forecast) % total	78%	70%	73%	65%	75%	64%	70%	59%	65%	51%	64%	50%	52%	51%	55%	42%	74%	78%
HIC (forecast) % total	0%	0%	0%	0%	2%	2%	0%	0%	2%	2%	1%	2%	5%	3%	2%	2%	5%	3%
Total Poverty Gap (TPG)																		
TPG ($bn 20005 PPP)	608	808	564	791	423	618	529	761	298	487	471	739	200	395	454	779	168	350
TPG as % global GDP	0.92	1.22	0.77	1.07	0.52	0.76	0.65	0.93	0.29	0.48	0.47	0.73	0.12	0.24	0.36	0.61	0.06	0.12

TABLE A4

Poverty Forecasts under Static Inequality, $10/day

$10/day	2010		2015				2020				2030				2040			
Static distributions			**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**		**Pessimistic**		**Optimistic**	
	S	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**	**S**	**NA**
Headcounts (millions)																		
East Asia and Pacific	1736	1799	1704	1863	1582	1775	1631	1827	1393	1575	1446	1626	726	977	1069	1361	247	375
Europe & Ctrl Asia	294	278	279	261	250	234	260	242	204	190	215	199	124	115	173	157	68	67
LatAm & Caribbean	379	393	388	401	360	373	392	405	338	349	386	397	284	291	362	371	210	222
M East and N Africa	251	250	343	337	332	326	368	362	345	340	408	401	327	318	430	429	279	257
North America	44	42	44	42	41	39	45	43	37	36	44	42	30	29	42	40	23	22
South Asia Region	1629	1604	1737	1709	1724	1667	1838	1789	1798	1704	2009	1910	1799	1509	2062	1961	1242	774
Sub-Saharan Africa	796	804	919	929	909	921	1032	1043	1001	1025	1272	1291	1192	1240	1524	1561	1291	1408
China	1203	1271	1128	1270	1026	1202	1041	1221	857	1009	853	1007	310	514	520	770	21	102
E Asia less China	534	527	577	593	557	573	590	606	536	566	592	620	416	463	548	591	226	273
India	1223	1199	1299	1272	1287	1232	1368	1319	1330	1242	1479	1381	1308	1024	1498	1401	771	300
S Asia less India	406	406	437	437	437	435	470	470	467	462	529	528	490	485	564	560	472	474
Total	**5130**	**5169**	**5415**	**5542**	**5198**	**5334**	**5566**	**5710**	**5115**	**5219**	**5780**	**5866**	**4481**	**4479**	**5662**	**5881**	**3361**	**3125**
LIC (current)	699	702	931	939	913	933	931	939	913	933	1115	1130	1048	1091	1293	1318	1096	1200
LIC (current) and fragile	555	557	745	752	730	748	745	752	730	748	880	893	821	858	1002	1023	826	922
MIC (current)	4291	4344	4498	4649	4098	4194	4498	4649	4098	4194	4538	4621	3362	3326	4256	4460	2219	1883
MIC (current) and fragile	531	538	658	667	640	643	658	667	640	643	781	791	709	713	898	908	693	729
LIC (forecast)	699	702	818	822	610	616	907	912	676	691	896	906	515	527	991	1008	171	186
MIC (forecast)	4291	4344	4386	4520	4109	4256	4459	4608	4024	4130	4511	4587	3063	2824	3558	3495	2704	2341
HIC (forecast)	140	124	210	200	479	462	199	190	415	398	373	373	902	1127	1113	1377	486	598
East Asia and Pacific	34%	35%	31%	34%	30%	33%	29%	32%	27%	30%	25%	28%	16%	22%	19%	23%	7%	12%
Europe & Ctrl Asia	6%	5%	5%	5%	5%	4%	5%	4%	4%	4%	4%	3%	3%	3%	3%	3%	2%	2%

LatAm & Caribbean	7%	8%	7%	7%	7%	7%	7%	7%	7%	7%	7%	7%	6%	6%	6%	6%	6%	7%
M East and N Africa	5%	5%	6%	6%	6%	6%	7%	6%	7%	7%	7%	7%	7%	7%	8%	7%	8%	8%
North America	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
South Asia Region	32%	31%	32%	31%	33%	31%	33%	31%	35%	33%	35%	33%	40%	34%	36%	33%	37%	25%
Sub-saharan Africa	16%	16%	17%	17%	17%	17%	19%	18%	20%	20%	22%	22%	27%	28%	27%	27%	38%	45%
China	23%	25%	21%	23%	20%	23%	19%	21%	17%	19%	15%	17%	7%	11%	9%	13%	1%	3%
E Asia less China	10%	10%	11%	11%	11%	11%	11%	11%	10%	11%	10%	11%	9%	10%	10%	10%	7%	9%
India	24%	23%	24%	23%	25%	23%	25%	23%	26%	24%	26%	24%	29%	23%	26%	24%	23%	10%
S Asia less India	8%	8%	8%	8%	8%	8%	8%	8%	9%	9%	9%	9%	11%	11%	10%	10%	14%	15%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
LIC (current) % total	14%	14%	17%	17%	18%	17%	17%	16%	18%	18%	19%	19%	23%	24%	23%	22%	33%	38%
MIC (current) % total	84%	84%	83%	84%	79%	79%	81%	81%	80%	80%	79%	79%	75%	74%	75%	76%	66%	60%
LIC (forecast) % total	14%	14%	15%	15%	12%	12%	16%	16%	13%	13%	16%	15%	11%	12%	18%	17%	5%	6%
MIC (forecast) % total	84%	84%	81%	82%	79%	80%	80%	81%	79%	79%	78%	78%	68%	63%	63%	59%	80%	75%
HIC (forecast) % total	3%	2%	4%	4%	9%	9%	4%	3%	8%	8%	6%	6%	20%	25%	20%	23%	14%	19%
Total Poverty Gap (TPG)																		
TPG ($bn 20005 PPP)	12842	20053	13302	20994	12327	19438	13473	21195	11328	17814	13359	20915	8713	13140	12765	19700	5942	9375
TPG as % global GDP	19.5	30.4	18.1	28.5	15.1	23.8	16.5	26.0	11.2	17.5	13.3	20.7	5.3	8.0	10.0	15.4	2.1	3.3

TABLE A5

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 A6

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 A7

Poverty, $10, 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	699	702	1117	1129	1056	1088	1115	1130	1048	1091	1119	1130	1057	1100
Least Developed Countries	763	765	1217	1232	1150	1188	1220	1233	1151	1192	1223	1233	1160	1201
All Fragile States	1086	1095	1661	1680	1534	1579	1661	1685	1530	1571	1675	1700	1524	1577
LIC Fragile States	555	557	881	893	827	856	880	893	821	858	883	893	829	866
LIC and non-converging	273	275	461	462	451	456	457	462	444	453	458	462	445	453
Conflict/Post-Conflict Countries	350	352	622	632	568	591	623	632	568	591	624	632	569	592
MIC and non-converging	685	694	882	875	780	769	861	867	766	740	828	835	732	717
MIC Fragile States	531	538	779	787	707	722	781	791	709	713	793	807	696	711
LIC and converging	386	387	547	552	504	526	547	554	502	528	550	554	509	537
Current LMICs	2426	2411	3064	2953	2764	2436	3015	2956	2581	2351	3036	2984	2518	2281
Current UMICs	1865	1932	1687	1710	1195	1195	1523	1666	781	975	1320	1526	563	759
All current MICs	4291	4344	4751	4663	3959	3631	4538	4621	3362	3326	4356	4510	3081	3040
All non-Fragile MICs	3760	3805	3971	3876	3252	2909	3757	3830	2652	2613	3564	3703	2386	2329
MIC and converging	3571	3613	3815	3734	3157	2832	3624	3700	2575	2558	3475	3620	2328	2296
IMF Emerging Market Economies	3759	3788	3894	3789	3210	2845	3676	3738	2621	2540	3474	3602	2352	2252
LICs in 2030			895	906	512	523	896	906	515	527	898	905	516	529
MICs in 2030			4685	4633	4313	4030	4511	4587	3747	3725	4359	4504	3490	3465
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	5130	5169	6010	5917	5107	4797	5780	5866	4481	4479	5514	5672	4149	4149

TABLE A8

Proportion of Global Poverty (%) in Fragile States (OECD 45 Countries), $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
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

TABLE A9

Proportion of Global Poverty (%) in Fragile States (OECD 45 Countries), $1.25 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	21.2	35.3	23.4	38.6	30.6	39.2	33.6	48.3	38.0	48.6	35.9	52.8	40.9	51.6
MIC Fragile States	10.9	11.4	12.7	16.6	21.4	18.0	21.6	19.6	24.5	19.7	20.1	17.9	20.4	16.4
All Fragile States	32.1	46.7	36.1	55.2	51.9	57.2	55.2	67.9	62.5	68.2	56.0	70.7	61.3	68.0
2030														
LIC Fragile States	21.2	35.3	22.8	35.7	24.6	35.0	35.5	48.9	36.4	47.0	38.3	51.3	37.7	49.7
MIC Fragile States	10.9	11.4	13.4	16.9	22.2	18.4	24.8	21.5	24.5	20.5	23.2	18.9	21.9	17.6
All Fragile States	32.1	46.7	36.2	52.6	46.8	53.4	60.2	70.4	60.9	67.4	61.5	70.2	59.7	67.2

TABLE A10

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 A11

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 A12

Distribution of Global Poverty, $2 Poverty Line, in 2025 and 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 (percentage 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 A13

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 A14

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

TABLE A15

Total Poverty Gap at $10, 2030 ($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	2102	3449	3236	5365	2633	4650	3213	5367	2605	4643	3211	5368	2573	4611
Least Developed Countries	2274	3718	3530	5864	2902	5126	3542	5866	2913	5107	3540	5864	2880	5073
All Fragile States	3101	4975	4583	7514	3607	6255	4585	7468	3603	6169	4543	7427	3491	6023
LIC Fragile States	1648	2721	2487	4178	1960	3566	2476	4180	1954	3564	2475	4181	1928	3536
LIC and non-converging	842	1382	1417	2305	1232	2096	1400	2304	1216	2109	1398	2304	1210	2103
Conflict/Post-Conflict Countries	991	1635	1775	2947	1448	2534	1775	2945	1447	2535	1773	2942	1443	2530
MIC and non-converging	1611	2435	2109	3168	1690	2490	2064	3093	1656	2437	1981	3001	1586	2367
MIC Fragile States	1453	2255	2097	3336	1646	2688	2108	3288	1649	2606	2068	3246	1563	2487
LIC and converging	1149	1880	1537	2560	1200	2153	1529	2560	1190	2131	1527	2561	1161	2103
Current LMICs	6709	9617	8198	10717	6015	6485	7440	10550	4932	6193	7295	10292	4642	5748
Current UMICs	3868	6771	3634	5731	2369	3701	2560	4798	1103	2203	1990	3958	775	1559
All current MICs	10578	16387	11832	16447	8384	10186	10000	15348	6035	8397	9286	14250	5418	7308
All non-Fragile MICs	9125	14133	9735	13111	6737	7497	7892	12060	4386	5791	7217	11004	3855	4821
MIC and converging	8887	13820	9617	13097	6672	7646	7835	12079	4359	5915	7205	11074	3812	4896
IMF Emerging Market Economies	9134	13984	9626	12845	6741	7407	7836	11766	4463	5686	7163	10711	3949	4734
LICs in 2030			2676	4494	1459	2481	2675	4495	1444	2479	2675	4495	1440	2480
MICs in 2030			11908	16667	9259	11960	10154	15560	6974	10159	9475	14524	6342	9063
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	12842	20053	15265	22069	11132	14984	13359	20915	8713	13140	12530	19659	7999	11931

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NOTES

1. See later discussion and Deaton (2010; 2011), Deaton and Heston (2010) and Klasen (2010).

2. See Chen and Ravallion (2012).

3. As, for example, in the estimates of the US$1/day global poverty headcount regularly produced by the World Bank (see Chen and Ravallion, 2008; 2012).

4. Figures refer to 2010. Figures vary slightly for other years due to availability of data. For example, in 1990 the model includes data for 167 countries, representing 96 per cent of the global population.

5. The GrIP model, therefore, provides the basis for comparison with and critique of other recent work on historical poverty and inequality statistics. However, because the focus of this paper is on poverty forecasts, extensive comparisons to other historical estimates are not the topic for this current paper but will be addressed in future publications.

6.Dhongde and Minoiu (2013) rightly 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. As we discuss later, since there are systemic differences between these means, we consider that a proper comparison would require adjustment of the poverty lines.

7. Data derived from GrIP corroborate this concentration of poverty in a relatively small number of countries. Number of countries accounting for 80 per cent of global poverty in 2010 (and figures in parentheses for 90 per cent of global poverty) by survey means method: $1.25 = 14 (and 27) countries, $2 = 14 (and 27); poverty in 2010 by NA mean, $1.25 = 19 (and 30), $2 = 17 (and 31).

8. We intend to address the issue of NA revisions as a separate matter in future work.

9. The paper also makes some projections based on combining growth and distributional changes to see what would allow the optimistic trajectory to be attained.

10. The assumption of static inequality (that growth occurs without changes in income or consumption distribution) probably overstates poverty reduction in rapidly growing economies, because there is evidence that rapid growth leads to increased inequality. For example, in China the growth of the last 20 years has been accompanied by a substantial increase in inequality.

11. A fuller explanation of the rationale behind these scenarios can be found in Sumner (2012a).

12. The main differences here being that Karver et al. and Sumner derive their forecast growth rates, as we do also in this paper, from the IMF's World Economic Outlook database, whereas Chandy and Gertz apply the Economist Intelligence Unit's (EIU's) forecast growth rates. Further, Karver et al. (2012) and Sumner (2012a) use GDP growth projections, and Chandy and Gertz use private consumption growth projections.

13. In GrIP, when producing static forecasts, we, like many others including Karver et al. and Chandy and Gertz, do not apply any such discount – or adjustment of NA/S ratios. However, we do apply adjustments that have a similar effect in our extrapolated dynamic forecasts by extrapolating not only recent trends income distribution but also trends in NA/S ratios for all included countries.

14. For 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).

15. 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 subnational – or 'within-country' – differences (differences arising from national distributions of income or consumption).

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

17. 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).

18. Contrary to the implication in Kharas and Rogerson (2012: 7) that a fuller treatment of the issues they address can be found in Chandy and Gertz (2011), the methodologies in these two papers are in fact very different, since Kharas and Rogerson use NA means, whereas Chandy and Gertz use Povcal's survey means. We are grateful to Laurence Chandy for pointing this out to us.

19. See p. 32 plus personal correspondence and Brookings website data.

20. Available at: <www.du.edu/~bhughes/ifs.html>.

21. The GrIP model avoids the first of these problems by using a method of linear interpolation that ensures that quintile, and upper and lower decile, data are 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 (i.e. how many have an annual income between $500 and $550 etc.) and then summing across all countries the total number within each income bracket.

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

23. 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. In accordance with most established practice, no attempts are made to modify income distributions to 'convert' them to consumption distributions. In general most authors concur that variations in the available data where income and consumption surveys can be directly compared mean that such conversions are too speculative to be justified.

24. 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 – issues which will be addressed in other forthcoming papers.

25. When selecting these scenarios we also considered similar scenarios used by others. Notably, Moss and Leo (2011) used the following scenarios: (a) Assume that 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 per cent of the 2016–2017 rate); (c) subtract 1 per cent from growth forecasts for all years from the current year; (d) use historical averages from the last 15 years (1995–2010) as a growth forecast for the 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 overestimate 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 option (b). However, given that our scenario halves growth from 2010, rather than 2017 in (b), and then also subtracts 1 per cent 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), although 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.

26. 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 USA. The 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's medium variant population forecasts from UNDESA (2011).

27. 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 per cent for the 14 economies over $1 trillion GDP PPP each, which accounted for 70 per cent 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 February 2012 update.

28. This applies to China, India and Indonesia only.

29. 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.

30. For example, and noted earlier, Kharas's (2010) estimate that in 2005 there was already no extreme ($1.25 a day in 2005 PPP $) poverty in India.

31 The calculations use survey means (Option 1) with filling of missing distributions where feasible. Effects of differences in population coverage and consumption coverage are adjusted for regionally.

32. Country income categorisations, in GNI $ per capita per annum (2010 constant $) are: low income (LIC) <= $1005; lower middle income (LMIC) $1006–3975; upper middle income (UMIC) $3976–12,275; high income (HIC) > $12,275. These compare to current thresholds as follows: low income $1025 or less; lower middle income $1026–4035; upper middle income $4036–12,475; and high income $12,476 or more.

33. Note that the results quoted in the rest of this paper cover only the 178 countries that in 2010 accounted for 96.6 per cent of global population. By contrast, the figures used in Table 6 to compare to the World Bank figures are compensated to adjust for missing population and consumption. That compensation is done by adjusting upwards the populations and consumption means in each geographic region pro rata to the missing millions based on WDI data on regional

aggregates. We cannot use compensated figures here because compensation inflates the individual country numbers, so that if we then aggregate these countries in different ways – i.e. not by geographic region – the results would become distorting and misleading. As a result the numbers presented in the rest of this paper are not truly 'global'.
In 2010 the countries included in this analysis covered 91.5 per cent of the total estimated global poverty headcount. So, very roughly, the poverty headcount numbers in this analysis might systematically understate the global figures by about 10 per cent.

34. Note that these figures are all calculated using the adjusted poverty line with NA means, as described earlier.

35. For comparison to the Kharas-Rogerson estimates cited earlier, in the optimistic forecast MICs (by forecast categorisation) will account for 59 per cent of $2 global poverty in 2025 when survey means are used, but only 50 per cent if NA means are used. Similarly in the pessimistic forecast MICs will account for 65 per cent (S) or 53 per cent (NA).

36. But note that in the tables in the Annex, China and India are included in the relevant aggregations. It is only in these maximum–minimum plots that we have separated them out from the aggregations.

37. Use of NA means also raises the proportion of global poverty in LICs and UMICs (notably China) and reduces the proportion in LMICs – principally this is because NA means reduce the poverty in India from 38 per cent (S) to 21 per cent (NA) of global poverty.

38 See<www.foreignpolicy.com/failed_states_index_2012_interactive>.

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