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Global poverty estimates: Present and future

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Abstract

Abstract. We review the recent empirical literature on global poverty, focusing on key methodological aspects. These include the choice of welfare indicator, poverty line and purchasing power parity exchange rates, equivalence scales, data sources, and estimation methods. We also discuss the importance of the intra-household resource allocation process in determining within-household inequalities and potentially influencing poverty estimates. Based on a sensitivity analysis of global poverty estimates to different methodological approaches, we show that existing figures vary markedly with the choice of data source for mean income or consumption used to scale relative distributions; and with the statistical method used to estimate income distributions from tabulated data.

Keywords: global poverty, household surveys, national accounts, tabulated data.
JEL Classification: I31, I32, O1.

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I. INTRODUCTION

Global poverty monitoring has been brought to the forefront of the international policy arena with the introduction of the Millennium Development Goals (MDGs). The first MDG proposes the elimination of severe poverty globally, and has been formulated as the goal of "halving the proportion of people with an income level below $1/day between 1990 and 2015." The adoption of the MDGs has led to renewed interest in estimating poverty at the national, regional, and global level. Nevertheless, the estimation of poverty at the global level is made difficult by data limitations and methodological challenges. For example, poverty estimates tend to be sensitive to the consumer price indices used to update poverty lines; the purchasing power parity (PPP) exchange rates required to make incomes and expenditure levels comparable across countries; and the statistical techniques employed to estimate income distributions.

Existing global poverty assessments put forth conflicting conclusions about the extent of poverty and the pace of poverty reduction. In this paper, we review the recent empirical literature on global poverty, focusing on key methodological issues. To analyze the sources of the discrepancies in estimates across different studies, we undertake a sensitivity analysis of global poverty rates and counts to changes in methodological approach. Specifically, we use a dataset with distributional information for 65 developing countries to estimate poverty in 1995 and 2005, alternating either the estimate of mean income that anchors national relative distributions, or the statistical technique used to estimate the income distribution from tabulations.

Our results suggests that a large share of the variation in estimated poverty levels and trends are attributable to the choice of surveys or national accounts as the primary data source for mean income (consumption). The estimation method for the income distribution from tabulations is also quantitatively important, although the trend of falling poverty over the past decade appears to be robust to the methodological approach. These findings suggest that efforts to uniformize data collection practices across countries, and to compile individual records from surveys into large-scale databases, are essential steps for advancing the debate and improving future global poverty statistics.

Some of the issues pertinent to our assessment have been discussed in the literature. For instance, Anand and Segal (2008) review the literature on global income inequality, highlighting the reasons that undermine confidence in existing estimates: measurement error in national accounts, survey data, and within-country price data; index numbers and multilateral comparisons for PPP estimates; and the lack of comparability of survey data across countries. Since poverty and inequality are different ways of analyzing the income distribution, most of the issues they discuss are also relevant to the measurement of global poverty. Our contribution is to bring to the fore aspects that so far have remained understudied, such as prevailing data sources for estimates of mean income or consumption (e.g., surveys or national accounts) and the type of available data (tabulations or individual records).

The rest of the paper is structured as follows. In Section II we discuss the steps involved in assessing poverty globally, focusing on the task of conceptualizing poverty and operationalizing the definition. Section III describes key empirical and methodological choices in global poverty assessments. Section IV presents a history of global poverty studies and discusses the existing estimates. In Section V we assess the sensitivity global poverty estimates to methodological choices, and we conclude in Section VI.

II. Conceptualizing Poverty

Global poverty assessments involve the following steps. The first step is to define poverty, i.e., to choose criteria based on which the poor can be identified. Sen (1976, 1993) defined poverty as absolute deprivation in terms of individual capabilities—the potential or personal advantage that an individual can attain. Accordingly, an individual's standard of living is reflected by his capabilities rather than the number of commodities she possesses or the level of utility she derives from consuming those commodities. The capability approach, though conceptually appealing, has proved difficult to apply empirically.[2]

Objective vs. subjective

Most of the empirical studies on global poverty take the objective approach to assessing well-being, using quantitative variables such as income, consumption, or indicators of child nutrition and health. Data on self-reported assessments regarding living conditions remain extremely scarce at the global level, with notable advances made by the 2000 World Development Report (WDR) "Voices of the Poor," which described the views on poverty of 60,000 individuals (World Bank, 2000), and Deaton's (2008) study of self-reported life satisfaction in 120 countries based on Gallup polls.[3]

Absolute vs. relative

In global analyses, the focus has traditionally been on absolute poverty, which concerns the cost of meeting a given standard of living (Bhalla, 2002; Chen, Datt, and Ravallion, 1994; Chen and Ravallion 1997, 2001, 2004, 2007, 2008; Kakwani and Son, 2006; Sala-i-Martin, 2006; Pinkovskiy and Sala-i-Martin, 2009). In contrast, relative measures of poverty aim to capture an individual's inability to participate in society, and are defined in relation to the overall distribution of income. Thus, the (relative) poverty line is anchored to the mean

[2] See Reddy, Visaria and Asali (2009) for an illustration.

[3] See also Gasparini and Gluzmann (2009) for a recent poverty assessment for Latin America and the Caribbean using Gallup World Poll data for 2006.

(median) income level. Relative poverty assessments are more common in richer countries. For example, the official poverty line for countries in the European Union is set at 60 percent of median income (Trinczek, 2007). Global relative poverty has empirically been studied by Ravallion and Chen (2009) and Nielsen (2009).

Unidimensional vs. multidimensional

Existing global poverty studies typically focus on unidimensional poverty, which is assessed based on a single welfare indicator (such as income or consumption). Multidimensional poverty is measured through a more inclusive approach that captures multiple dimensions of well-being (e.g., access to basic social services, educational attainment, health status, availability of shelter, and participation in the labor market). However, micro-data of the kind required to estimate multidimensional poverty across countries remain sparse.[4] An early attempt to estimate global poverty in a multidimensional framework (including income, health, and education) was the Human Development Index (HDI)—first published for a large number of countries in the 1997 Human Development Report (HDR). The most recent HDR proposes a Multidimensional Poverty Index that draws on a larger number of living standard, health and education variables to assess deprivation at the household level in 104 countries.

Welfare indicator: Income vs. consumption

In the traditional money-metric approach to global poverty measurement, poverty is assessed based on income or consumption. Choosing between the two measures of welfare often depends on the availability and quality of existing data. Countries follow different practices when conducting household surveys. For example, Latin American and Central and East European countries are more likely to collect data on income, whereas surveys in Asian, African and Middle Eastern countries focus on consumption (Chen and Ravallion, 2004). Global poverty estimates are derived by aggregating national income and expenditure data after making adjustments to either of the two variables.[5] Nevertheless, both income and consumption variables suffer from substantial measurement error (Deaton, 2003), as discussed further in Section III.

Poverty lines: National vs. international

If national poverty lines were consistent with a uniform definition of poverty, the number of global poor could be estimated by adding up corresponding poverty headcounts. In practice, this is not feasible because national poverty lines often correspond to different definitions of

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[4] Although not available for every country and every year, micro surveys that systematically collect non-income information across countries include the Demographic and Health Surveys and the Living Standards Measurement Surveys.

[5] For example, Chen and Ravallion (2001) rescale mean income by one minus the saving rate to obtain mean consumption for countries that only undertake income surveys (Chen and Ravallion, 2001, p. 7). The rescaling, however, is found to have little impact on estimated trends or inter-regional comparisons.

poverty. Furthermore, only few countries monitor poverty systematically, leading to data gaps in national statistics.[6] Global poverty is instead estimated using international poverty lines (such as $1/day and $2/day) that are translated into countries' local currencies using PPP exchange rates, and that are moved backward and forward in time using national inflation rates. The $1/day poverty line[7] is close to the average of PPP-adjusted national poverty lines of the poorest 15 nations in the world (Ravallion, Chen, and Sangraula, 2008).[8]

Several studies have discussed the challenges posed by the international poverty lines and their conversion into local currencies, arguing that GDP PPPs are inadequate for poverty assessment as they do not reflect the consumption patterns of the poor[9] and the poverty thresholds do not capture the real requirements of human beings (Reddy and Pogge, 2010). Ackland, Dowrick, and Freyens (2008) have shown that the choice of price index to calculate the PPP exchange rates leads to large differences in global poverty counts. PPP estimates are also updated at long intervals through the International Comparison Program (ICP), which only surveyed prices of commodities and services world-wide in 1985, 1993, and 2005. (China participated for the first time in the 2005 ICP round.) The 2005 update led to substantial revisions of historical series of PPP-adjusted GDP for a number of countries. Furthermore, estimates of global poverty and inequality were revised upwards using the new PPPs (Chen and Ravallion, 2008; Milanovic, 2009),[10] while world growth estimates were revised downwards over 2002–07 to reflect countries' updated weights in global GDP (Elekdag and Lall, 2008).

To sum up, the standard approach to global poverty measurement focuses on unidimensional absolute poverty (where the welfare indicator aiming to capture the standard of living) and estimates it by applying international poverty thresholds to objective distributional data on income or consumption from household surveys.

III. KEY METHODOLOGICAL CHOICES

Here, we focus on three methodological issues that are crucial for global poverty assessments but have received relatively less attention in the literature: (i) the use of equivalence scales to calculate individual income (consumption) from the household aggregate; and the presence of intra-household inequality in the allocation of resources; (ii) the choice of mean income

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[6] For example, the World Development Indicators (WDI) 2009 database includes national poverty statistics for only 5 percent of the countries.

[7] Refers to $1.00 at 1985 PPPs, $1.08 at 1993 PPPs, and $1.25/day at 2005 PPP.

[8] In turn, these national poverty lines are typically anchored to a nutritional norm representing 2,100 calories per person per day plus a non-food allowance roughly equal to non-food expenditures of individual close to the caloric cut-off.

[9] Deaton and Dupriez (2008) adjust PPP exchange rates by re-weighting the consumption basket to address this problem.

[10] A number of recent studies have critically reviewed global poverty estimates based on the 2005 ICP PPPs (see, e.g., Himanshu, 2009; Klasen, 2009).

estimate (from household survey vs. national accounts) that anchors national relative distributions; and (iii) the estimation method of the income distribution from tabulated data.

A. Equivalence Scales and Intra-Household Inequality

Although the relevant unit in global poverty assessments is the individual, data is often available only at the household level. To obtain consumption levels for each individual in a household, household consumption is typically divided by the number of household members. However, this procedure rests on the unrealistic assumption that all household members have equal consumption levels. In reality, the consumption requirements to achieve the same level of welfare of children and the elderly are different than those of adults. Furthermore, consumption of some goods can be economized among members, the household providing opportunities for economies of scale. Equivalence scales, which compute the adult-equivalent consumption level of household members depending on their caloric intake, can be used to model consumption heterogeneity among household members. To obtain per capita consumption, total household consumption is then divided by the number of equivalent adults rather than the number of household members.

There is no global poverty assessment to date that attempts to use consumption per equivalent adult, although national and regional analyses often do.[11] One reason is that the necessary adjustments require access to individual records, whereas much data is only available in tabulated form (Shorrocks and Wan, 2008). A second reason is that there is no consistent source of equivalence scales across countries. Even if individual record data were available for the entire world, equivalence scales would have to be constructed for each country to account, e.g., for relative differences in the cost of children (Milanovic, 2005, p. 18–19).

While it is likely that using equivalence scales in the assessment of global poverty would change existing estimates, the magnitude of any adjustments is unclear *ex ante*. However, evidence from individual country studies suggests that the impact of incorporating equivalence scales in studies of global poverty could be important. For example, Buhmann et al. (1988) use data from the Luxembourg Income Study for ten OECD countries to show that the use of equivalence scales as well as the choice among them systematically affects estimates of absolute and relative poverty. The degree of sensitivity varies across countries, although rank-orderings by poverty and inequality level are relatively robust (see also Haughton and Khandker, 2009; Burniaux et al., 1998). This leads the authors to conclude that "because of these sensitivities one must carefully consider summary statements and policy implications derived from cross-national comparisons of poverty and/or inequality" (p. 140).

[11] See Burniaux et al. (1998) for a study of poverty in OECD countries using alternative equivalence scales.

In a global assessment of poverty, equivalence scales-related adjustments would be largest for countries that experienced the steepest changes in demographics and household characteristics (Burniaux et al., 1998; Betson, 1996, 2004). This is the case of China—the main driver of poverty reduction in the developing world.[12] Between 1990 and 2005, the average household size in China fell from 3.4 to 3 (Chamon and Prasad, 2010, pp. 98) and the share of the population older than 65 increased from 5.6 to 7.5 percent.[13] We summarize the evolution of regional demographic trends in recent decades in Table 1. Overall, the share of young population has significantly fallen over the period while that of population above 65 has markedly risen. East Asia and sub-Saharan Africa (SSA) have registered the largest and smallest demographic transformations, respectively. There are also important cross-regional differences in average household size but little empirical evidence on how it changed over time.[14]

A related issue is that adult equivalence scales themselves are imperfect for estimating individual consumption, since the latter does not only depend on demographics, but also on the nature of the resource allocation process within households. Adult equivalence scales assume that there is no household inequality. Although the empirical evidence on patterns of intra-household resource allocation remains scant, the results of recent studies are informative. Lise and Seitz (2008) show that using standard equivalence scales (which ignore intra-household inequality) leads consumption inequality in the UK to be underestimated by 30 percent—a result explained by the fact that the gender earnings gap translates into a consumption gap inside the household. Furthermore, British data reveal that household inequality has declined markedly since the 1970s as the share of income earned by wives has increased. These findings suggest that true consumption distributions for women and men are markedly different from those obtained using adult equivalence scales.

These concerns are particularly relevant for developing countries where poverty rates are higher and the allocation of resources within households also depends on cultural norms. A study of the number of decision makers in Turkish households shows that while consumption patterns in the average Turkish household are consistent with a multi-person model, households in Eastern Turkey, where traditional values prevail, are ‘unitary’ in the sense that one decision maker allocates resources to the other members of the household (Kapan, 2009). The single-decision maker model cannot be rejected in subsamples of households in which women do not participate in the labor market or whose children are female. The genders of children and the wives’ outside options are therefore important determinants of the allocation of resources within the household. This has implications for the assessment of welfare in

[12] Outside China, the number of poor has increased since 1981 for all poverty lines higher than $1.25/day (Chen and Ravallion, 2008).
[13] WDI (2006).
[14] A notable exception is Bongaart (2001), who analyzed household structure in developing nations using 43 household surveys over 1990-1998. He concluded that convergence to smaller households was proceedings slowly in the developing world based on the available data.

countries where labor market participation for women remains limited or patriarchal values are dominant.

Could intra-household inequalities play an important role in the assessment of global poverty? Table 2 reports regional trends in gender inequalities in education and labor market participation since 1990. There are important regional differences in the male-to-female ratio of literacy and primary completion rates and not all regions are closing the education gap at the same rate. Substantial reductions in the gender education gap (measured by these indicators) were attained over 1990–2004 in the Middle East and North Africa (MENA) region, East and South Asia, and SSA. If education and employment opportunities play the role of shifters of female voice in the household, inequalities in the intra-household allocation of resources are also changing, and standard equivalence scales would fail to capture that. [15]

In our sensitivity analysis we ignore the issues of equivalence scales and intra-household inequality due to insurmountable data limitations, recognizing that they provide a potentially fruitful venue for future research as more and better survey data become available.

B. Survey vs. National Accounts-based Data

A second key methodological issue concerns the *source of data* for welfare indicators such as consumption: the estimates can be drawn either from household surveys (HS) or from national accounts statistics (NAS). HS are typically organized by national statistical agencies and collect information from representative households on consumption expenditures and/or personal disposable income. As a result, HS-based consumption can suffer from flaws in survey design (Deaton and Grosh, 2000) and lack of representativeness, recall bias,[16] underreporting among the poor, and poor response rates among the wealthy (Mistiaen and Ravallion, 2003; Deaton, 2005). Expenditure surveys are also more expensive to undertake than income surveys, as they require multiple visits to the participating household and consumption diary-keeping over a specified period. In contrast, NAS-based consumption is computed in the national accounts by subtracting net exports, investment, and government expenditure from national income.

How does the choice of estimate matter for poverty assessment? It has been documented that HS-based and NAS-based consumption differ both in level and growth rates. NAS consumption is higher than HS consumption (Deaton, 2001, 2005; Ferreira and Ravallion, 2008a) and grows faster than it. The level effect is due to the former including imputed rent on home-owners, imputed value of non-marketed items such as gifts, food produced and

[15] Another important determinant of intra-household inequality is the sex ratio. Recent papers document the marked worsening of the sex ratio imbalance in China over the past decades (Wei and Zhang, 2009), which could also play a role in determining the allocation of household resources and influence estimated poverty.
[16] For example, a substantial debate over the accuracy of Indian poverty estimates was caused by changes in the recall period (see, e.g., Deaton and Kozel, 2005 and Dhongde, 2007).

consumed at home, and consumption of non-profit organizations. In contrast, the latter can only imperfectly evaluate home-produced consumption, as market prices for self-produced goods can only be collected from distant (often urban) markets, and rents in rural areas with thin housing markets are imputed based on prices from vibrant (urban) rental markets. NAS consumption grows faster than HS consumption because it includes goods and services that are rarely consumed by the poor and because richer households are less likely to participate in surveys (Deaton, 2005).[17] Furthermore, pure measurement error, differences in coverage, the presence of an informal sector, and differences in consumption deflators, cause further discrepancies (Ravallion, 2003).[18]

The World Bank measures consumption poverty hence uses HS-based data whenever possible. Missing observations are interpolated across years using growth rates of per capita private consumption from the national accounts (Chen and Ravallion, 2008). Another approach is to scale HS estimates by the ratio between NAS income and HS income. Other studies circumvent this problem by relying solely on NAS data: Bhalla (2002) and Bourguignon and Morrisson (2002) employ NAS consumption as the welfare aggregate, whereas Sala-i-Martin (2006) uses NAS income. Deaton (2005) notes that if HS are wrong and NAS are correct, then using HS to estimate poverty will tend to underestimate the decline in poverty. Similarly, if HS are correct and poverty is estimated using NAS then the results will overstate the pace of poverty reduction.

C. Estimation methods

The last methodological issue we discuss relates to the method of estimation of the income distribution. An important hurdle in estimating long-term trends in regional or global poverty is the lack of individual record data (unit data) for multiple countries and years. Efforts to undertake household surveys are often interrupted by conflict or undermined by poor statistical infrastructure. Surveys are sometimes available at periods far apart, and the individual records are unavailable in the public domain. Researchers often rely on published summary statistics—grouped frequency tables or ‘tabulated data’—representing income (consumption) shares for a small number of population groups.[19] Virtually all the studies on global poverty and inequality use a mix of individual records and tabulated data, especially for large countries such as China and India (Milanovic, 2005; Chen and Ravallion, 2008).

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[17] Ferreira and Ravallion (2008b) emphasize that the NAS-means method is unacceptable when doing an urban-rural poverty assessment.

[18] Similar considerations arise when income poverty is estimated using per capita GDP from the NAS rather than per capita income from HS.

[19] A comprehensive income distribution database (of income shares and Gini coefficients) is the UNU-WIDER World Income Inequality Database (WIID), which draws on multiple sources of information for developed, developing, and transition countries (Deininger and Squire, 1996; the Luxembourg Income Study; the Transmonee data by UNICEF/ICDC; Central Statistical Offices; and other research studies.) Another source is the collection of survey-based data at the World Bank, which systematically compiles cross-country distributional data and disseminates national, regional, and global poverty statistics on its research studies and on its Povcalnet website (http://go.worldbank.org/NT2A1XUWP0).

Others derive national income distributions solely from summary statistics in (Bourguignon and Morrisson, 2002; Bhalla, 2002; Kakwani and Son, 2006; Sala-i-Martin, 2006; Ackland, Dowrick, and Freyens, 2008; Pinkovskiy and Sala-i-Martin, 2009).

The global poverty literature proposes two methods for estimating national income distributions from tabulated data. The first approach is parametric: the Lorenz curve or the income density is parameterized using a simple functional form. For the Lorenz curve, the most widely used parameterizations are the General Quadratic ('GQ', proposed by Villasenor and Arnold, 1989) and the Beta (Kakwani, 1980).[20,21] For the income density, the two-parameter log-normal distribution is the preferred candidate (Babones, 2003; Pinkovskiy and Sala-i-Martin, 2009), but other parameterizations have been proposed. These include a maximum entropy estimator for a density from the exponential family (Wu and Perloff, 2005, 2007) and the Generalized Beta-2 distribution parameterization for the income density (Chotikapanich, Griffiths, and Rao, 2007; Chotikapanich, Rao, and Tang, 2007). Neither of the latter two approaches has been used in global poverty assessments.

The second approach for estimating national income distributions from tabulated data is nonparametric (Sala-i-Martin, 2006; Zhang and Wan, 2006; Ackland, Dowrick, and Freyens, 2008). The method consists of applying the kernel density estimator on the tabulated data (expressed as mean incomes for several population groups), and has the advantage that no functional assumption needs to be made regarding the underlying data generating process. Nevertheless, kernel density estimation requires specifying additional parameters (such as the kernel and bandwidth), which can have a large impact on the resulting estimate if applied to tabulated data rather than individual records.

Recent studies have assessed the performance of traditional methods in estimating the underlying distribution from tabulated data, and have concluded that parametric approaches provide more reliable estimates than nonparametric ones. For example, Minoiu and Reddy (2009) used Monte Carlo simulations on data from plausible income distributions to find that the GQ and Beta Lorenz curve parameterizations perform well in estimating poverty and inequality from tabulations, with biases rarely exceeding one percentage point.[22] Further, Minoiu and Reddy (2008) empirically assessed the small-sample bias of the kernel density estimator to find that errors in the density and poverty estimates are often large, and depend crucially on the choice of bandwidth and on the position of the poverty line relative to the population median.

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[20] Parametric approaches have been used in Bhalla (2002), Pritchett (2006), Kakwani and Son (2006), and the World Bank's studies on global poverty.

[21] Implementation of these methods can be done using the computational tools Povcal and SimSIP developed by the World Bank (Datt, 1998). Povcalnet poverty estimates are obtained using these Lorenz curve parameterizations.

[22] To further improve on these techniques, Shorrocks and Wan (2008) develop an algorithm which ensures that the simulated sample matches the moments of the tabulated data.

To our knowledge, no study to date has systematically assessed the variations in global poverty estimates to changes in the estimation method. An exception is Pinkovskyi and Sala-i-Martin (2009), who report correlation coefficients between national poverty rates corresponding to different parameterizations for the income density. While these correlations capture common trends in the series being compared, they preclude an assessment of level differences. We attempt to fill this gap in the sensitivity analysis presented in Section V.

IV. Review of Global Poverty Studies

A. A Chronology

Global poverty assessments were undertaken for the first time at the World Bank, which started to systematically compile cross-country distributional data in the late 1970s.[23] Earlier contributions include Paukert (1973), who tested the Kuznetz hypothesis using relatively comparable income distribution data for 56 nations. Two decades later, Ravallion, Datt, and van de Walle (1991) estimated developing world poverty in 1985 using data from only 22 countries and an extrapolation model for 64 other nations. Chen, Datt, and Ravallion (1994) and Ravallion and Chen (1997) expanded the coverage to 44 and 67 countries, respectively, to measure progress in reducing poverty between the mid-1980s and the early 1990s.

The first paper to rely entirely on survey data—a mix of individual records and tabulations—was Chen and Ravallion (2001), who assembled distributional information from 265 surveys in 83 developing nations.[24] In their most recent study, Chen and Ravallion (2008) derived their poverty statistics from 675 nationally representative surveys in 115 developing nations. (For a chronology of global poverty studies since the late 1970s, see Table 3.) The scale of this study reflects the remarkable progress that has been made in compiling cross-country income distribution data over the past decades.

To illustrate how much information is available to study the long-run global distribution of income in public databases, we compiled data from the World Income Inequality Database (UNU-WIDER WIID 2008), Povcalnet, WDI, and the updated Dollar and Kraay (2002) dataset.[25] In all, income shares for population quintiles and Gini coefficients are available for

[23] Distributional data for only 20 countries were published in the World Development Report between 1979 and 1995. The 1996 World Development Report included distributional data for 67 lower- and middle-income countries.

[24] To fill in the gaps, countries without data were imputed their regional neighbors' average poverty rate.

[25] To construct the dataset, we started with the UNU-WIDER WIID dataset and retained all observations regardless of data quality. Unique country-year observations from the other datasets are subsequently added to obtain an 'augmented' WIID world distribution dataset. Only a few observations available in the Dollar and Kraay (2002) and WDI are not already present in the other sources. The final dataset includes information on income shares for population quintiles and Gini coefficients (as reported in the original databases).

154 countries over 1960–2007 and are drawn from 3,031 underlying surveys (Table 4). While high-income countries have almost 30 surveys per country (out of 47 possible), middle- and low-income countries have 20 and 10 surveys on average. Survey coverage is best in South Asia and Latin America and worst in SSA and the MENA region. Data availability has increased markedly from some 30 country-surveys in the 1960s to 123 in the 1990s. The number of countries for which data is available rose from 17 in the 1960s to three time as many in the 1990s (Figure 1).

B. Global Poverty Estimates: What Do They Tell Us?

Published poverty figures offer conflicting conclusions about the extent of poverty and the pace of poverty reduction. Take, for example, the latest two studies: Chen and Ravallion (2008) and Pinkovskiy and Sala-i-Martin (2009) (henceforth, 'CR' and 'PS'). Both studies present estimates of the global income distribution, but differ markedly in terms of underlying data, interpolation techniques, choice of and data source for the welfare indicator, and estimation method. Table 5 summarizes the authors' choices. Key differences include the scope of the analysis (developing world vs. world) and the fact that CR estimates consumption poverty, while PS focus on income poverty (and adjust consumption shares accordingly to correspond to income shares). Once the income (consumption) shares are assembled, CR anchor the country-specific distributions mostly to HS consumption estimates, while PS use NAS per capita income (GDP). Finally, CR use a mix of individual records and tabulated data, on which they estimate the Lorenz curve using the GQ method, while PS rely solely on tabulations to estimate national income distributions using the log-normal parameterization.

Both studies employ PPP estimates from the latest round of the ICP and estimate poverty relative to the standard thresholds \$1/day, \$2/day, etc. Chen and Ravallion (2008) estimate that in 2005 nearly 26 percent of the population in the developing countries was poor, the global poverty count fell by 520 million individuals since 1981. In contrast, Sala-i-Martin presents a \$1/day poverty rate of 2.4 percent in 2005, corresponding to a reduction in the poverty count of almost 350 million individuals since 1981. Figure 2 plots estimates of the global poverty rate corresponding to different studies and PPPs. While level estimates vary substantially, most authors document a falling trend over the past decades, though the extent of the decline remains subject to debate.[26]

V. Sensitivity Analysis

A. Survey- vs. National Accounts-based Poverty Estimates

We assess the sensitivity of global poverty estimates to changes in the *data source* of mean income (or consumption). The aim is to determine the variation in global poverty estimates

[26] See, e.g., Reddy and Minoiu (2007).

attributable to the use of HS vs. NAS data while all the other parameters of the analysis are held constant. The difference this choice makes to the final estimates is not obvious from existing studies because, as discussed previously, these differ in many other dimensions.

Before proceeding to the results, we give a short description of the task of estimating poverty. When individual record data are unavailable, we must use tabulations that capture the country's relative income distribution and come in the form of income shares for population quintiles or deciles. For example, we know the share of national income possessed by population quintiles, deciles, or any number of population groups. (Typically, income shares are available for at most 20 groups.) To obtain a distributional profile (i.e., the average income for each group) the relative distribution must be anchored to a mean level of income (or consumption)—which can be drawn either from HS or NAS. Since mean income is only used to scale the relative distribution, its effect is simply to shift the income distribution along the income axis (Figure 3).

Our main data source for is the Povcalnet database, which is particularly fit for our sensitivity analysis because it includes HS estimates of average consumption.[27] In addition, Povcalnet includes relative distributions for a large number of countries.[28] We take 1995 and 2005 as benchmark years, and select 65 countries for which distributional information is available in those years.[29] Poverty rates and counts are estimated for international poverty lines ranging between \$1/day and \$2.5/day; and the GQ parameterization for the Lorenz curve. Note that we are largely replicating the World Bank methodology described in detail in Chen and Ravallion (2008).[30] NAS income and consumption are taken from the Penn World Tables Mark 6.3 (Heston, Summers and Aten, 2009).

We report unweighted and population-weighted summary statistics for PPP-adjusted consumption and income over 1995–2005 in Table 7. Mean consumption from surveys is the lowest estimate of the three aggregates, with NAS consumption exceeding it by a large factor. The gap between the two estimates has increased over time: while NAS consumption was larger than HS consumption by a factor 1.6 or 1.9 in 1995 (for the weighted and

[27] Povcalnet reports either HS mean consumption or mean income, depending on the nature of the underlying survey. Mean consumption is available for two thirds of the sample; when consumption is unavailable, we use income. (For a detailed discussion, see Chen and Ravallion, 2008, p. 15).

[28] We find no systematic differences between the income and consumption shares (i.e., a regression of the shares against an indicator variable for the type of survey yields a statistically insignificant coefficient—the results are available upon request). Therefore, we use the raw data without further adjustments.

[29] For countries with no information in 1995 or 2005, we use data from adjacent years, namely 1993–97 and 2003–07. For China, India, and Indonesia, Povcalnet reports rural/urban distributional data, but there is no PPP-adjusted income (consumption). We therefore replace use national tabulations instead from alternative sources such as the WDI and WIID. Our sample thus covers slightly more than 70 percent of the total world population. (For the full list of countries, see Table 6.)

[30] Nevertheless, the estimates we present should not be interpreted as unbiased estimates of the true extent of poverty, since we simply use a sample of countries for which both HS and NAS data are available to investigate robustness to changes in mean income (consumption) estimates.

unweighted samples, respectively), this has increased to 1.8 or 2.3 by 2005. The level difference between survey consumption and NAS income (GDP) is even higher. Furthermore, survey consumption has registered the lowest increase of the three aggregates, with an average annual growth rate of 0.9 percent over the period, compared to 3.1 percent for NAS consumption and 3.8 percent for GDP.[31]
Given that the mean income (consumption) estimates serve as anchor for the relative distributions of countries, these level- and growth differences between the various estimates will affect both the estimated extent and trend of global poverty over the period. The results confirm this intuition (Table 8). For example, in 2005, the \$1/day consumption poverty rate was 29 percent using HS consumption, and only 5.9 percent using NAS consumption. The difference between HS- and NAS-based poverty estimates is large and increases still by 2005, reflecting the different growth rates of the various welfare aggregates. As a result, the pace of (\$1/day consumption) poverty reduction varies between 16 percent and 32 percent depending on the data source. While the falling trend of the poverty headcount ratio appears robust across poverty lines, poverty appears to have increased when we use the absolute headcount as the relevant measure. Specifically, HS-based consumption yields an upward trend in \$2/day and \$2.5/ day poverty, while NAS consumption and income yield falling poverty headcounts. The reason for this difference is that the growth rate of welfare measured from the surveys is insufficient to compensate for population growth and lead to a decline in poverty.[32]

We conclude that a large share of the variation in published estimates of poverty is attributable to the choice of data source for mean income (or consumption): HS vs. NAS. On average, survey consumption is (substantially) lower than its national accounts counterparts, generating (substantially) higher poverty rates. Furthermore, survey consumption (income) grows slower than NAS consumption (income), leading to a slower estimated pace of poverty reduction.

B. Estimation Methods

The second choice regards the estimation method of income distributions from tabulated data. From the wide range of techniques available, we select six parametric and six nonparametric options, as follows: the GQ and Beta parameterization for the Lorenz curve; the two-parameter log-normal and three-parameter Singh-Maddala parameterizations for the

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[31] These estimates are of comparable magnitudes to those reported by Deaton (2005), the differences being driven by a different sample composition and period of analysis; and different PPPs. Deaton uses 277 surveys over 1979–2000 to find that NAS consumption is on average 20 percent higher than survey consumption in the full sample that includes advanced economies; and grew over 1990–2000 at an average growth rate of 2.3 percent compared to 4.5 percent for its NAS counterpart. Our analysis goes one step further in that we examine the impact of these discrepancies on poverty estimates.
[32] The results are consistent with the headcount estimates reported by Chen and Ravallion (2008) for higher poverty lines, which increased over the period 1981–2005.

income density function; the Beta and log-normal parametric approaches with the Shorrocks and Wan (2008) correction; and the kernel density estimator with six alternative data-driven bandwidths. The parametric techniques are described in detail in Abdelkrim and Duclos (2007) and Datt (1998) while the nonparametric ones in Wand and Jones (1995). Before presenting the results, we briefly discuss each technique.

All of the methods above can be used to estimate the Lorenz curve or the income distribution from aggregate distributional information. The GQ and Beta approaches assume functional forms for the Lorenz curve, the estimation of which involves a simple regression to estimate the parameters. Similarly, the log-normal and the Singh-Maddala functions are theoretical distributions that have been shown to approximate well real-world income data (Bandourian, McDonald and Turley, 2003). The procedure proposed by Shorrocks and Wan (2008) aims to improve on the initial distribution generated from the estimated Lorenz curve by correcting the initial sample of incomes to match the group means from the original data.

Finally, the kernel density estimator is a nonparametric smoothing technique aimed at estimating the income density. The simplest nonparametric technique for estimating the density is the histogram; the kernel density estimator produces a 'smooth' histogram. While the method has the advantage of not assuming a (potentially restrictive) functional form, it requires specifying a bandwidth which controls the smoothness of the estimated density. The bandwidth is the interval around each point of estimation where the estimator looks for information about the density at that point (income). The statistical literature proposes a number of 'optimal' bandwidths which minimize the mean squared error of the estimator, among which we select six examples. Importantly, different bandwidths lead to different results; hence it is good practice to assess the robustness of any nonparametric estimate to changes in the bandwidth.

We report global poverty rates and counts for 1995 and 2005 using three poverty lines ($1/day, $1.45/day and $2.50 day) and our original sample of 65 countries (Tables 9–10). The $1/day poverty headcount ratio varies in 1990 between 4.2 percent and 8.9 percent, or by a factor of 2.1. Similarly, in 2005 it varies by a factor of 3.2 depending on the method employed. The large variations in level-estimates of poverty across different methods are also apparent for the higher poverty lines. However, the falling trend in the poverty rate is robust across estimation methods, with declines ranging by 13 to 25 percentage points for the poverty lines considered. Similarly, the absolute headcount varies by between 200 and 237 million people in 1990; and 131 to 272 million people in 2005. For this indicator too the trend of poverty reduction is robust across estimation methods, but the extent of the decline varies between 102 and 165 million people.

We conclude that the estimation methods of the income distribution from tabulated data play an important role in determining the estimated extent and trend of poverty. While the direction of the trend seems robust, the extent of poverty and the extent of the decline in poverty vary markedly with the method employed. This variation is informative in that it can provide lower and upper bounds on poverty estimates, reflecting the uncertainty associated with the statistical technique used to generate them.

VI. Conclusions

Global poverty monitoring is an important item on the international development agenda, with the first MDG aiming to reduce the share of '$1/day poor' people in the world by 50 percent by 2015. In this paper, we reviewed the recent empirical literature on global poverty statistics with the aim to construct a coherent picture of the current state of knowledge and bring to the fore issues that remain relatively understudied.

First, we characterized the standard approach to measuring poverty at the international level: this is unidimensional, it focuses on absolute poverty, and uses objective (income or expenditure) data. Attempts to depart from this approach—for example, to measure long-run multidimensional poverty or use subjective information—are rare and face important data-related obstacles. We also discussed key methodological issues in global poverty measurement, focusing on equivalence scale and the role played by intra-household inequalities for poverty and interpersonal inequality. Though conceptually important and often acknowledged in existing global poverty assessments, these issues remain outside their scope because of data limitations.

We also undertook a sensitivity analysis of global poverty estimates to changes in the data source for mean income (or consumption) that is used to anchor relative income distributions; and to the statistical method used to estimate the income distribution from tabulated data that is often available in lieu of individual records. Our results suggest that a large share of the variation in estimated poverty levels and trends are attributable to the choice of surveys or national accounts as the primary data source for mean income (consumption). This choice alone appears to account for the bulk of level-differences in global poverty rates and counts across existing studies. The choice of statistical technique to estimate poverty from tabulated data is also important. Nevertheless, the falling trend of poverty over the past decades appears robust to the choice of methodological approach.

Overall, our results suggest that the debate concerning global poverty would benefit from improvements in data collection practices across countries, and the compilation of unit-record data from surveys into large-scale databases. Promising areas of future research include assessing long term trends in absolute and relative human wellbeing using multidimensional frameworks, and incorporating information from subjective data.

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VIII. APPENDIX

Table 1. Demographic trends and gender inequalities by region, 1970–2004

Demographic trends	1970	1980	1990	2004	% change 1970-2004
Population ages < 14 (% of total)					
East Asia & Pacific	40.6	36.9	30.3	24.5	*-39.7*
Europe & Central Asia	29.3	26.3	26.4	20.2	*-30.8*
Latin America & Caribbean	42.5	39.8	36.4	30.4	*-28.4*
Middle East & North Africa	45.1	44.3	43.3	34.0	*-24.6*
South Asia	41.0	39.5	37.8	33.8	*-17.6*
Sub-Saharan Africa	44.8	45.4	45.6	43.7	*-2.4*
Population ages > 65 (% of total)					
East Asia & Pacific	4.1	4.5	5.1	6.8	*66.2*
Europe & Central Asia	7.8	9.4	9.0	11.6	*48.9*
Latin America & Caribbean	4.2	4.4	4.7	5.9	*42.3*
Middle East & North Africa	3.8	3.6	3.5	4.2	*10.4*
South Asia	3.6	3.9	4.1	4.8	*34.4*
Sub-Saharan Africa	2.9	2.9	2.9	3.1	*4.7*
Average household size					
Asia			5.14		
Europe & Central Asia			3.60		
Latin America & Caribbean			4.76		
Middle East & North Africa			5.65		
Sub-Saharan Africa			5.25		

Source: World Development Indicators (2006) and authors' calculations.

Table 2. Gender inequalities by region, 1990–2004

Gender inequalities	1990	2004	% change 1990-2004
Female participation in the labor force			
East Asia & Pacific	44.10	43.84	*-0.6*
Europe & Central Asia	45.59	44.93	*-1.4*
Latin America & Caribbean	34.03	40.24	*18.2*
Middle East & North Africa	22.94	27.17	*18.5*
South Asia	30.64	29.33	*-4.3*
Sub-Saharan Africa	43.03	42.19	*-1.9*
Ratio of male to female primary completion rates			
East Asia & Pacific	1.02	1.02	*0.0*
Europe & Central Asia	0.99	1.01	*1.5*
Latin America & Caribbean	0.96	0.99	*2.3*
Middle East & North Africa	1.17	1.04	*-11.3*
South Asia	1.33	1.09	*-17.8*
Sub-Saharan Africa	1.17	1.18	*1.0*
Ratio of male to female literacy rates			
East Asia & Pacific	1.24	1.09	*-12.2*
Europe & Central Asia	1.04	1.01	*-3.1*
Latin America & Caribbean	1.03	1.02	*-1.8*
Middle East & North Africa	1.67	1.26	*-24.6*
South Asia	1.76	1.55	*-11.8*
Sub-Saharan Africa	1.50	1.30	*-13.5*

Source: World Development Indicators (2006), Bongaarts (2001) for average household size, and authors' calculations.

Table 3. Chronology of global poverty studies

	# of countries	% of developing world population	# of surveys	Poverty estimates are reported in:
Grouped data and individual records				
Ahluwalia, Carter, and Chenery (1979)	36[1/]			1975
Ravallion, Datt, and van de Walle (1991)	22[2/]			1985
Chen, Datt, and Ravallion (1994)	40			1985, 1990
Ravallion and Chen (1997)	67	85%	109	1987, 1990, 93
Ravallion and Chen (2001)	83	88%	265	1987, 1990, 93, 96, 98
Ravallion and Chen (2004)	97	93%	454	1981, 84, 87, 1990, 93, 96, 99, 2001
Ravallion and Chen (2007)	100	93%	500	1981, 84, 87, 1990, 93, 96, 99, 2002, 04
Ravallion and Chen (2008)	115	90%[3/]	675	1981, 84, 87, 1990, 93, 96, 99, 2002, 05
Grouped data				
Dowrick and Akmal (2001)	47	70%		1980, 1993
Bourguignon and Morrisson (2002)	33			1850, 1970, 1890, 1910, 29, 59, 60, 70, 80, 92
Sala-i-Martin (2002a, 2002b)	97+28[4/]	90%		1970, 1980, 1990, 1998
Sala-i-Martin (2004)	111+28[4/]	93%		1970, 75, 1980, 85, 1990, 95, 2000
Sala-i-Martin (2006)	110+28[4/]	93%		1970-2000
Pinkovskiy and Sala-i-Martin (2009)	191	98%	1069	1970-2006
Individual records				
Milanovic (2002)	91, 119	86%, 91%	216	1988, 1993

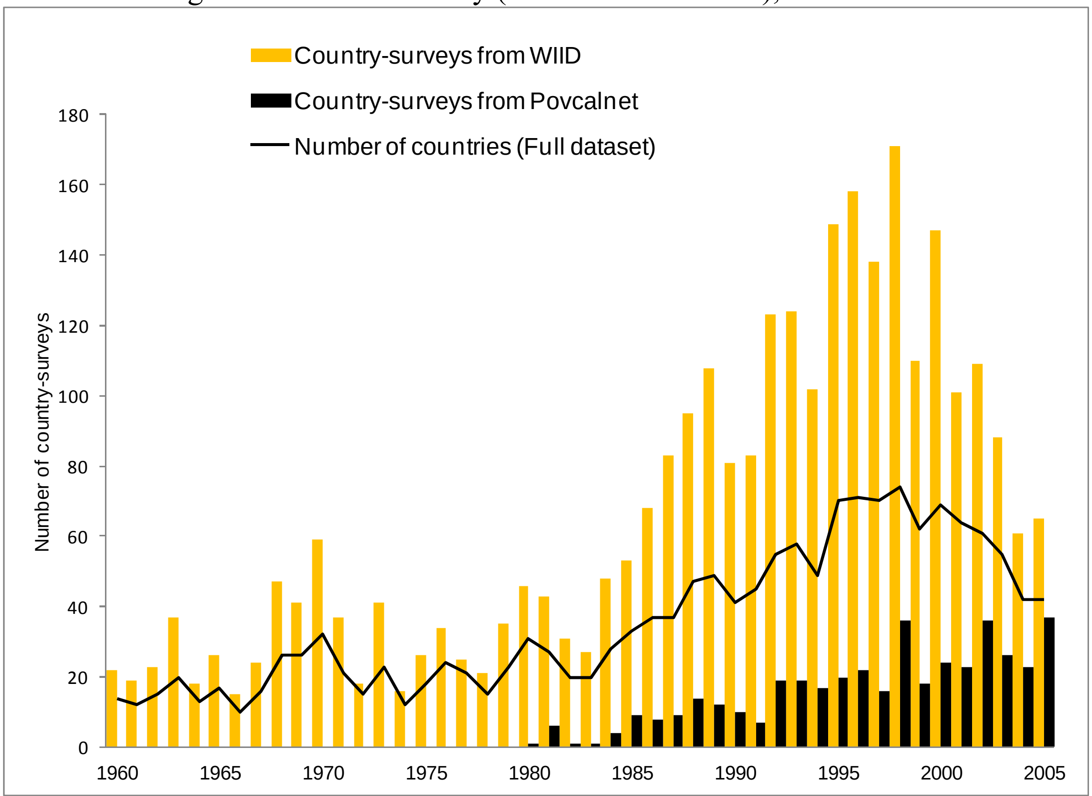
1/ "Fairly reliable" data was only available for 25 of the 36 countries (Ahluwalia, Cartner, and Chenery, 1979, footnote. 1); for the remainder, the data were estimated using cross country comparisons.
2/ Poverty is estimated for an additional 64 countries using an extrapolation model.
3/ The coverage varies between 74 percent for the MENA region; and 98 percent for SSA.
4/ Distributional information exists for 97 (or 111) countries, depending on the study. It is imputed for 28 countries.

Table 4. Data available for global analyses, 1960–2007

DATABASE	# countries	# surveys	# surveys per country	coverage
World Income Inequality Database (WIID)	140	2211	15.8	1960-2006
Povcalnet [1/]	116	447	3.9	1980-2007
World Development Indicators (WDI)	90	162	1.8	1982-2005
Dollar and Kraay (2002)	79	211	2.7	1961-1999
Total	**154**	**3031**	**19.7**	**1960-2007**
of which: Low-income	39	369	9.5	
Middle-income	78	1629	20.9	
High-income	37	1027	27.8	
of which: East Asia & Pacific	12	209	17.4	
Europe & Central Asia	22	450	20.5	
Latin America & Caribbean	24	757	31.5	
Middle East & North Africa	9	90	10.0	
OECD and high-income non-OECD	37	1027	27.8	
South Asia	6	165	27.5	
Sub-Saharan Africa	44	327	7.4	

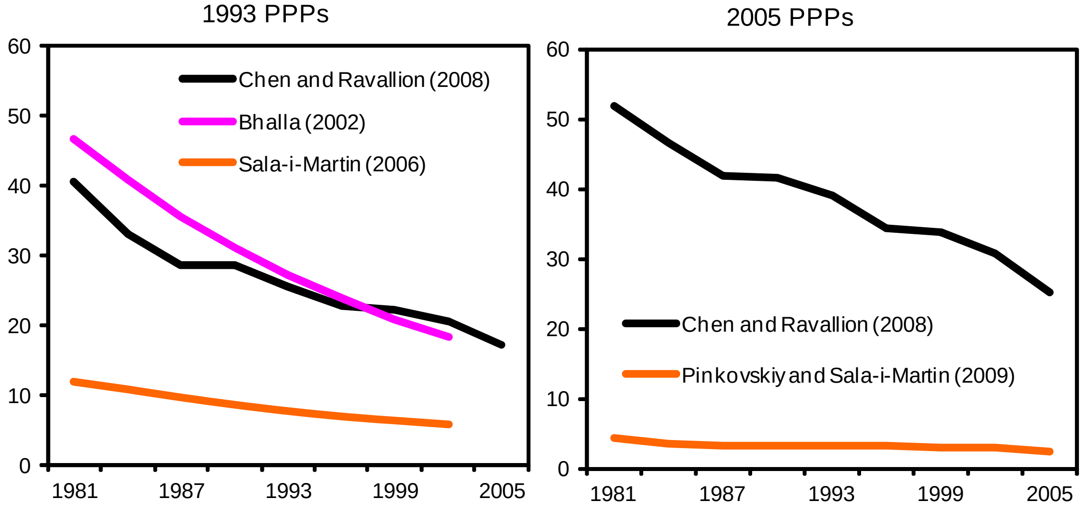
Source: Authors' calculations.
1/ Povcalnet reports rural and urban distributional data for three countries: China, India, and Indonesia.

Figure 1. Data availability (WIID and Povcalnet), 1960–2005



Source: Authors' calculations.

Figure 2. Global poverty rates from different sources (%), 1981–2005

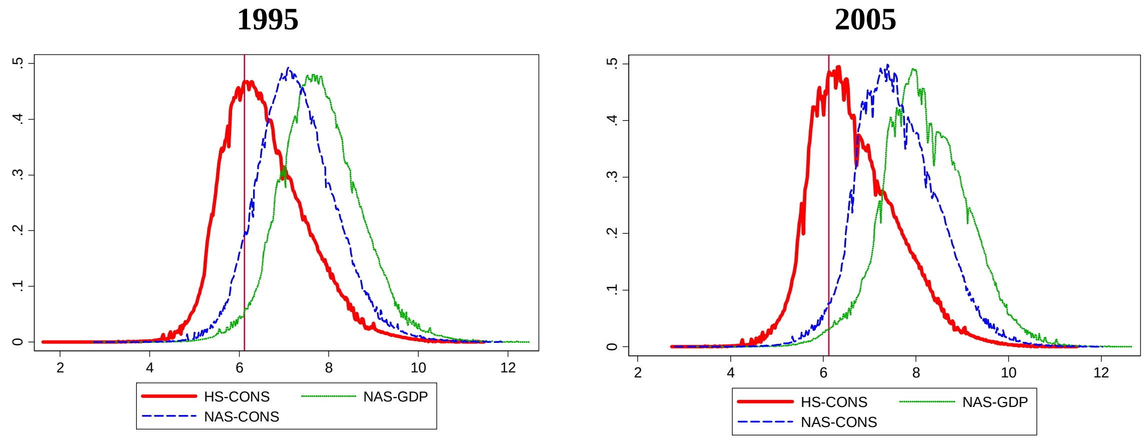


Notes: The various estimates are not strictly comparable because of differences in methodologies (see text). Furthermore, Chen and Ravallion (2008) and Bhalla (2002) compute the $1/day poverty rates relative to the developing world population, whereas Sala-i-Martin uses the total world population as denominator. The figures are for the year listed or the closest available year.

Table 5. Methodological differences between recent studies

Characteristics of the analysis	Chen and Ravallion (2008)	Pinkovskiy and Sala-i-Martin (2009)
Scope of analysis	Developing world	World
Number of countries	115	191
% of (developing) world population	90	97.9
Number of surveys	675	1069
Type of data	Individual records, grouped data	Grouped data
Interpolation/extrapolation techniques	Yes, to line up surveys with reference years	Yes, of Gini coefficients for missing years
Welfare indicator	Consumption	Income
Source of data for welfare indicator	HS; when HS unavailable, use NAS with adjustment	NAS
International poverty line	$1.25/day (at 2005 PPP)	$1/day to $10/day (at 2005 PPP)
Estimation method	Generalized Quadratic (or Beta) for the Lorenz curve	Log-normal assumption for the density

Figure 3. Impact of survey vs. national accounts mean income/consumption on the global distribution



Source: Authors' calculations.
Note: The world income distribution has been obtained by integrating national distributions estimated assuming zero within-quintile inequality; and smoothed using a kernel density estimator with Gaussian kernel and optimal bandwidth (Silverman, 1986). The vertical line is placed at $1/day international poverty line.

Table 6. List of countries included in the sensitivity analysis (N=65)

Albania	Dominican Rep.	Kenya	Panama
Argentina	Ecuador	Kyrgyz Republic	Paraguay
Armenia	Egypt	Latvia	Peru
Azerbaijan	El Salvador	Lithuania	Philippines
Bangladesh	Estonia	Madagascar	Poland
Belarus	Ethiopia	Malawi	Romania
Bolivia	Georgia	Malaysia	Russian Federation
Brazil	Guinea	Mali	Senegal
Bulgaria	Honduras	Mexico	Slovenia
Burkina Faso	Hungary	Moldova, Rep.	Thailand
Cambodia	India	Mongolia	Turkey
Central African Republic	Indonesia	Nepal	Uganda
Chile	Iran	Nicaragua	Ukraine
China	Jamaica	Niger	Uruguay
Colombia	Jordan	Nigeria	Venezuela, RB
Costa Rica	Kazakhstan	Pakistan	Vietnam
			Zambia

Table 7. Summary statistics for survey and national accounts mean income/consumption

	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Unweighted		**1995**				**2005**		
HS-CONS	1,922	1,350	287	6,668	2,148	1,512	409	8,241
NAS-CONS	3,095	1,879	625	8,205	4,104	2,611	624	11,714
NAS-GDP	4,957	3,431	791	13,436	6,669	4,927	834	22,004
Population-weighted								
HS-CONS	1,222	998	287	6,668	1,331	1,065	409	8,241
NAS-CONS	2,256	1,421	625	8,205	3,051	1,733	624	11,714
NAS-GDP	3,877	2,377	791	13,436	5,614	3,064	834	22,004

Source: Povcalnet for survey-based consumption (HS-CONS) and Penn World Tables (PWT) Mark 6.3 for national accounts-based consumption (NAS-CONS) and income (NAS-GDP). All figures expressed in 2005 international US$ (chain-weighted series in the case of PWT data).

Table 8. Sensitivity of global poverty estimates to data source for mean income or consumption (survey vs. national accounts)

	1995			2005			Reduction over 1995-2005		
	HS-CONS	NAS-CONS	NAS-GDP	HS-CONS	NAS-CONS	NAS-GDP	HS-CONS	NAS-CONS	NAS-GDP
Headcount ratio (%)								(%)	
$1.00/day	29.0	5.9	1.4	24.3	1.7	0.9	-16	-32	-72
$1.25/day	38.6	10.7	2.7	33.7	2.9	1.5	-13	-44	-73
$1.45/day	45.1	14.8	4.2	40.2	5.0	2.0	-11	-53	-66
$2.00/day	58.5	25.8	9.6	54.2	13.5	3.7	-7	-62	-47
$2.50/day	66.6	35.1	15.6	62.8	21.4	5.5	-6	-65	-39
Absolute headcount (millions)								(millions)	
$1.00/day	1,219	250	58	1,140	78	44	-6	-24	-69
$1.25/day	1,621	452	112	1,579	136	70	-3	-37	-70
$1.45/day	1,893	620	177	1,887	234	93	0	-48	-62
$2.00/day	2,458	1,082	405	2,540	635	174	3	-57	-41
$2.50/day	2,798	1,476	654	2,945	1,002	259	5	-60	-32

Source: Authors' calculations using the Generalized Quadratic parameterization of the Lorenz curve (Vilasenor and Arnold, 1989; Datt, 1998). Estimates obtained using the Stata package DASP Version 2.1 (Abdelkrim and Duclos, 2007).

Table 9. Sensitivity of global poverty estimates to the estimation method (selected poverty lines)

	1995			2005			Reduction over 1995-2005		
	$1.00/day	$1.45/day	$2.50/day	$1.00/day	$1.45/day	$2.50/day	$1.00/day	$1.45/day	$2.50/day
	Headcount ratio (%)						(%)		
Parametric methods									
GQ	5.9	14.8	35.1	1.7	5.0	21.4	-72	-66	-39
Beta	4.2	11.0	29.9	1.3	3.3	17.6	-70	-70	-41
Beta*	4.4	11.1	30.3	1.3	3.7	17.0	-70	-67	-44
Log-normal	5.3	11.8	29.7	2.3	5.7	17.6	-57	-52	-41
Log-normal*	4.3	11.0	30.3	1.6	4.2	16.9	-62	-62	-44
Singh-Maddala	5.5	12.3	34.0	2.3	5.6	20.6	-58	-55	-39
Nonparametric methods									
Kernel *Silverman*	5.4	12.5	31.4	1.6	5.2	19.0	-69	-58	-40
Kernel *Normalscale*	6.0	13.1	31.7	2.0	5.7	19.2	-67	-56	-39
Kernel *Oversmooth*	8.9	16.6	32.9	4.1	9.2	22.7	-55	-45	-31
Kernel *DPI-1*	7.6	14.9	32.2	2.8	7.2	20.6	-64	-52	-36
Kernel *DPI-2*	8.1	15.6	32.2	3.2	7.7	21.5	-60	-51	-33
Kernel *DPI-3*	8.6	15.7	32.2	3.4	7.9	21.6	-61	-49	-33
	Absolute headcount (millions)						(millions)		
Parametric methods									
GQ	250	620	1,476	78	234	1,002	-171	-385	-474
Beta	176	461	1,257	59	156	827	-116	-304	-430
Beta*	183	468	1,273	62	174	796	-121	-294	-477
Log-normal	225	497	1,247	108	268	827	-116	-229	-420
Log-normal*	179	462	1,273	76	197	793	-103	-265	-480
Singh-Maddala	232	518	1,430	109	263	966	-123	-256	-464
Nonparametric methods									
Kernel *Silverman*	226	527	1,321	77	244	891	-149	-282	-430
Kernel *Normalscale*	254	551	1,332	95	269	901	-159	-282	-431
Kernel *Oversmooth*	375	697	1,381	190	429	1,066	-185	-268	-315
Kernel *DPI-1*	318	625	1,351	129	335	967	-189	-290	-384
Kernel *DPI-2*	340	655	1,355	150	361	1,008	-190	-294	-347
Kernel *DPI-3*	362	658	1,354	157	372	1,012	-205	-286	-342

Source: Authors' calculations for selected poverty lines. Estimates obtained using the Stata package DASP Version 2.1 (Abdelkrim and Duclos, 2007) for parametric methods; and the *kdens* Stata command (Jann, 2005) for the nonparametric (kernel) approach. The welfare aggregate is NAS-consumption. * labels estimates obtained using the Shorrocks and Wan (2008) iterative correction procedure, which ensures that the sample moments of the estimated distribution are the same as those of the raw data. Six estimates are presented for the kernel density estimator (applied to quintile means), each corresponding to a different 'optimal' bandwidth (in italics). These include the Silverman (1986) bandwidth, the *normalscale* bandwidth—a variant of Silverman (1986) which assumes normality of the log-income distribution, the *oversmooth* bandwidth (a good starting point for bandwidth fine-tuning) and three *direct-plug in* (DPI) bandwidths that iteratively estimate the density (Wand and Jones, 1995).

Table 10. Variation in global poverty estimates due to estimation method

	$1.00/day	$1.45/day	$2.50/day	$1.00/day	$1.45/day	$2.50/day	$1.00/day	$1.45/day	$2.50/day
	Headcount ratio								
Ratio between maximum and minimum estimate	2.1	1.5	1.2	3.2	2.7	1.3	0.8	0.6	0.7
Difference between max and min estimate (percentage points)	5	6	5	3	6	6	17	25	13
	Absolute headcount								
Ratio between maximum and minimum estimate	2.1	1.5	1.2	3.2	2.7	1.3	0.5	0.6	0.7
Difference between max and min estimate (millions)	200	237	229	131	273	272	102	157	165

Source: Authors' calculations.