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# Global Poverty Estimates: A Sensitivity Analysis

*Shatakshee Dhongde and Camelia Minoiu*

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# Global Poverty Estimates: A Sensitivity Analysis

**Prepared by Shatakshee Dhongde and Camelia Minoiu**[1]

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**Abstract**



Current estimates of global poverty vary substantially across studies. In this paper we undertake a novel sensitivity analysis to highlight the importance of methodological choices in estimating global poverty. We measure global poverty using different data sources, parametric and nonparametric estimation methods, and multiple poverty lines. Our results indicate 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 different estimation methods. The decline in poverty over the past decade is found to be robust across methodological choices.

JEL Classification Numbers: C14, D31, F01, I32, O10

Keywords: global poverty, sensitivity analysis, household surveys, national accounts, income distribution, international poverty line

Authors' E-Mail Addresses: shatakshee.dhongde@econ.gatech.edu and cminoiu@imf.org

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[1] Shatakshee Dhongde is Assistant Professor in the School of Economics at the Georgia Institute of Technology; Camelia Minoiu is Economist at the IMF Institute. We would like to thank Florent Bresson, Alina Carare, Gaston Gelos, Richard Palmer Jones, Mahvash S. Qureshi, Sanjay G. Reddy, and participants at the Brooks World Poverty Institute Conference "Ten years of war against poverty: What have we learned since 2000 and what should we do 2010–20?" in Manchester (September 2010) and the 80th Southern Economic Association Meeting in Atlanta (November 2010) for useful discussions and comments.

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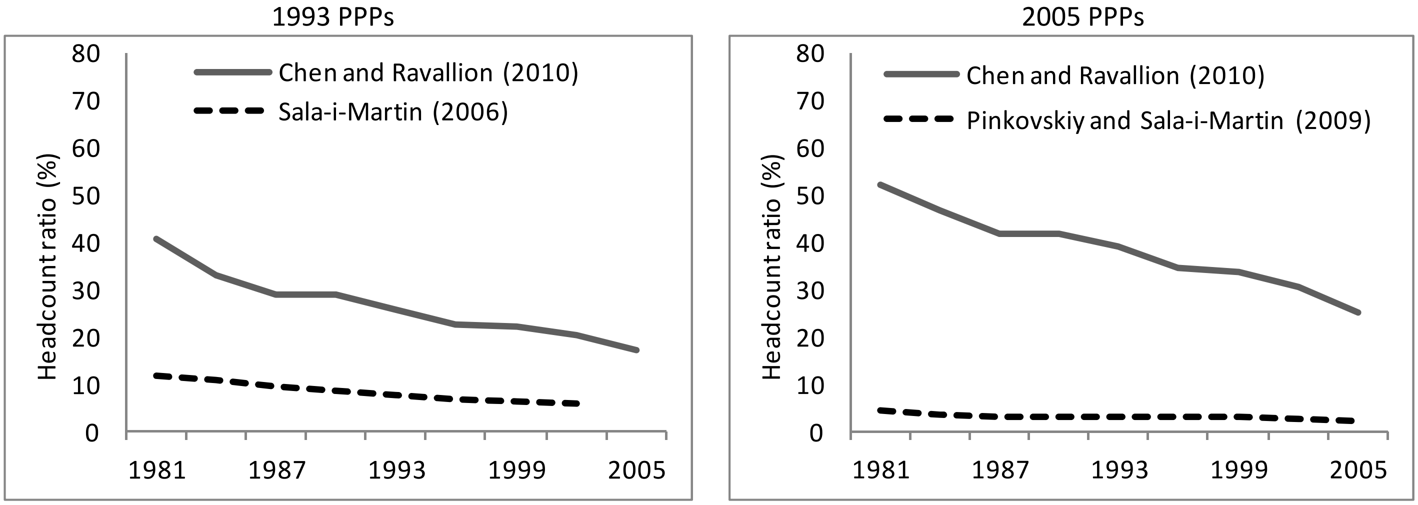
# I. INTRODUCTION

Global poverty monitoring has been brought to the forefront of the international policy arena with the adoption of the Millennium Development Goals (MDG) by the United Nations. The first MDG proposes reducing global poverty by the year 2015 and is stated as "halving the proportion of people with an income level below $1/day between 1990 and 2015" (United Nations, 2000). Progress towards attaining this MDG is monitored using global poverty estimates published by the World Bank and a number of independent scholars. The process is not only expensive (Moss, 2010) but also mired with conceptual, methodological, and data-related problems (Klasen, 2009).

Current estimates of global poverty proposed in the literature differ in magnitude as well as in the rate of change in poverty. Consider, for instance, Chen and Ravallion (2010) and Pinkovskiy and Sala-i-Martin (2009)—two studies that estimate global poverty using the international poverty line of $1/day (see Figure 1). Chen and Ravallion (2010) estimate that in 2005 nearly 26 percent of the population in the developing countries was poor, and the global poverty count fell by 520 million individuals since 1981. By contrast, Pinkovskiy and Sala-i-Martin (2009) estimate poverty to have been ten times lower in 2005, which implies a reduction of almost 350 million individuals since 1981. Although there is general agreement that global poverty has declined over the years, the estimated level of poverty and rate of poverty decline vary substantially across studies.

This paper aims to contribute to the debate on global poverty not by providing a new set of estimates, but by addressing two important questions. First, we ask why estimates from different studies differ so much. As we unravel the various assumptions made by researchers, we show that global poverty estimates are simply not comparable across studies. For instance, they differ in terms of underlying data sources, number of countries included, welfare metric, adjustments to mean incomes, and statistical methods employed to estimate the income distribution. Given this variety of methodological choices, we arrive at our second question: Can we assess the impact of different approaches on the resulting poverty estimates? Since global poverty estimation requires making multiple assumptions simultaneously, we aim to isolate and assess separately the relative importance of each such assumption by undertaking a novel sensitivity analysis.

**Figure 1 Estimates of global poverty between 1981 and 2005**




Notes: The poverty rates are not strictly comparable across studies because of differences in methodological approach (see Section II.B.).

An important hurdle in estimating long-term trends in global poverty is the lack of high-quality, consistent survey data. The poor are those individuals whose income is less than or equal to some threshold set by the poverty line. If countries had complete information on every individual's income then with an agreed-upon global poverty line, identifying the poor would be a straightforward exercise. However, there are severe data limitations.

Data on income is typically collected through household surveys (HS) of nationally representative samples. However, survey data are often available for periods far apart and suffer from a number of inconsistencies (regarding sampling and interviewing techniques, definitions of variables, and coverage) that render them incomparable across countries. Nonetheless, they are the sole source of information on the relative distribution of incomes in a country—that is, the shares of national income possessed by different population groups (quintiles, deciles). HS also provide estimates of mean income/consumption which are used to scale the income shares to obtain mean incomes by population group. A more readily-accessible and consistently-recorded source of information are national account statistics (NAS) which also provide aggregate income or consumption estimates and are available for most countries on a yearly basis.

A key methodological choice in estimating global poverty is whether to use data on mean income/consumption from HS or NAS or whether to combine data from the two sources. Some studies in the literature analyzed the sources of discrepancies between the levels and growth rates of income/consumption data from HS and NAS (Ravallion, 2003; Deaton, 2005). However these studies did not measure the precise effect of using HS and NAS data on global poverty levels and trends. In order to determine how sensitive global poverty estimates are to alternate data sources, we estimate global poverty by anchoring relative distributions alternately to HS and NAS estimates of mean income and consumption. This is our first sensitivity exercise.

The second sensitivity exercise concerns the choice of statistical method used to estimate income distributions from grouped data, that is, data on mean income or consumption for population groups (quintiles, deciles). We estimate global poverty by estimating each country's distribution using different methods. These include the General Quadratic (GQ) and the Beta Lorenz curve, and the lognormal and Singh-Maddala functional forms for the income density function.[2] In addition to these parametric specifications, we also consider the nonparametric kernel density method whose performance we assess in conjunction with four different bandwidths—a parameter that controls the smoothness of the income distribution.

As a benchmark, we follow the World Bank methodology to the extent possible and estimate global poverty in 1995 and 2005—the latest year for which data is available for many countries. Data on the relative distribution of income across population deciles is collected for 65 countries from the World Bank's poverty monitoring website PovcalNet. Our sample covers more than 70 percent of the total world population and includes all countries for which both HS and NAS data are available in both years. Global poverty is estimated using international poverty lines ranging from \$1/day to \$2.5/day to provide further insight into how methodological choices impact poverty rates at different income cutoffs.

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[2] See Villasenor and Arnold (1989) for the GQ Lorenz curve, Kakwani (1980) for the Beta Lorenz curve, Gibrat (1931) for the lognormal density specification and Maddala and Singh (1976) for the Singh-Maddala density specification.

Our results are twofold. First, a large share of the variation in estimated poverty levels and trends can be attributed to the choice between HS and NAS as the source of data. 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 HS and NAS do not tend to converge in higher income countries. Second, the choice of statistical method used to estimate the income distribution affects poverty levels to a lesser extent. A comparison of poverty estimates across parametric and nonparametric techniques reveals that the commonly used lognormal specification consistently underestimates poverty levels. While there is little doubt that the proportion of poor declined between 1995 and 2005, our results underscore the fact that global poverty counts are highly sensitive to methodological approach.

The remainder of the paper is structured as follows. Section II consists of a review of the literature on global poverty. We explain the sensitivity analysis and introduce the data in Section III. In Section IV we discuss the sensitivity of global poverty estimates to methodological approach. Conclusions are presented in Section V. The statistical techniques used in the exercise are described in the Appendix.

## II. Literature Review

There is a large and diverse body of literature on global poverty. We have compiled this literature in two broad categories. The first consists of studies discussing conceptual and methodological challenges in defining poverty; the second includes studies mainly focused on providing estimates of global poverty. There is considerable overlap between the two types, with some studies falling in both categories.

### A. Conceptualizing Global Poverty

A number of conceptual issues, which we briefly review here, are at the core of global poverty analysis.[3] Measuring poverty inherently involves choosing between alternate

[3] See Ravallion (1996), Deaton (2001), Ferreira and Ravallion (2008) and Dhongde (2010) for detailed discussions.

notions of poverty. The subjective approach defines poverty using an individual's perception of own well-being and utilizes data from self-reported assessments of living conditions.[4] Thus the subjective approach involves a value judgment as to what it means to be poor. By contrast, the objective approach defines poverty based on measurable indicators of well-being. Traditionally, global poverty has been defined in terms of deprivation in a single dimension, namely income or consumption. Global poverty has been measured either in absolute terms, using a pre-defined poverty line based on the cost of living (Chen and Ravallion 2001, 2004, 2010), or in relative terms by anchoring the poverty line to mean or median income levels (Nielsen, 2009; Ravallion and Chen, 2009). However based on Amartya Sen's broader notion of capabilities (Sen 1976, 1993), recent efforts have been aimed at estimating global poverty using multiple dimensions. For instance, the United Nations Development Programme's new multidimensional poverty index measures global poverty as a combination of deprivation in three dimensions using ten indicators of well-being (Human Development Report, 2010).

Within the objective approach, global poverty is defined in terms of an absolute income cutoff equal to $1/day or $2/day. The $1/day poverty line was introduced by the World Bank in 1990 and roughly corresponds to the average of the purchasing power parity (PPP)-adjusted national poverty lines of the 15 poorest countries in the world (Ravallion, Chen and Sangraula, 2009). This poverty line provides a conservative definition of global poverty and has been criticized for not capturing the real requirements of well-being (Klasen, 2009; Reddy and Pogge, 2010). The $1/day poverty line which was based on 1985 PPPs was revised to $1.08/day based on 1993 PPPs and $1.25 based on 2005 PPPs. Using this last update, Chen and Ravallion (2010) found that global poverty had previously been significantly underestimated.[5] Critics have also noted that the PPP exchange rates used in global poverty monitoring are inadequate because they are designed for national income accounting purposes and do not reflect the consumption patterns of the poor. In a sensitivity

[4] For example, see the World Development Report "Voices of the Poor" (World Bank, 2000), which described the views on poverty of 60,000 individuals and Deaton's (2008) study of self-reported life satisfaction in 120 countries based on Gallup polls.

[5] Deaton (2010) argued that the large upward revision in global poverty was a consequence of the inappropriate updating of the global poverty line.

analysis similar to ours, Ackland, Dowrick and Freyens (2008) found that PPP rates calculated using different methods led to large differences in global poverty counts. A similar conclusion was arrived at by Deaton and Dupriez (2011) who proposed alternative PPP rates based on the expenditure patterns of the poor.

In addition to these conceptual challenges, the exercise of measuring global poverty is fraught with empirical problems. Objective poverty estimates can be drawn either from HS or NAS income or consumption data—a key issue discussed in detail in the next section. Furthermore, Latin American and Central and East European countries collect data on income, whereas Asian, African, and Middle Eastern countries collect data on consumption (Chen and Ravallion, 2004). Both income and consumption variables suffer from substantial measurement error and combining data from income and consumption surveys poses comparability issues (Deaton, 2001, 2003). Data on consumption at the household level is converted to per capita simply by dividing total consumption by the number of household members, ignoring economies of scale in consumption or inequality in the intra-household allocation of resources.[6] To date there is no global poverty assessment that tackles these issues.

### B. Estimating Global Poverty

Table 1 provides a chronology of studies estimating (objective) global poverty levels. An early attempt in the 1970s was undertaken by Ahulwalia, Carter and Chenery (1979) who estimated poverty in 36 developing countries. Global poverty monitoring received an impetus from the World Bank in the 1990s with its efforts to compile cross-country distributional data. Ravallion, Datt and van de Walle (1991) estimated global poverty in 1985 using distributional data from 22 countries. Chen, Datt and Ravallion (1994) and Ravallion and Chen (1997) expanded the data coverage and measured poverty between the mid-1980s and the early 1990s. Chen and Ravallion (2001) was the first global poverty analysis that relied entirely on survey data. Chen and Ravallion (2004) provided poverty estimates going back to

[6] For a discussion on equivalence scales and inequality in intra-household resource allocation, see Haddad and Kanbur (1990) and Szekely et al. (2004).

early 1980s and created PovcalNet—a web-based interactive tool providing access to distributional data across countries. As more information became available, studies such as Bhalla (2002) and Sala-i-Martin (2006) proposed alternative estimates. The most recent contribution is Chen and Ravallion (2010) who derived their poverty statistics over 1980–2005 from 675 nationally representative surveys in 115 developing nations.

**Table 1 Chronology of global poverty studies**

| Global poverty studies | Years | No. of countries[1] | Database[2] |
|---|---|---|---|
| Ahluwalia, Carter, and Chenery (1979) | 1975 | 25 | World Bank Data Bank |
| Ravallion, Datt, and van de Walle (1991) | 1985 | 22 | World Bank |
| Chen, Datt, and Ravallion (1994) | 1985–1990 | 40 | World Bank / WDR |
| Ravallion and Chen (1997) | 1987–1993 | 67 | World Bank / WDR |
| Chen and Ravallion (2001) | 1987–1998 | 83 | World Bank |
| Bhalla (2002) | 1950–2000 | 149 | World Bank, PWT |
| Chen and Ravallion (2004) | 1981–2001 | 97 | World Bank |
| Sala-i-Martin (2006) | 1970–2000 | 110 | WIID, PWT |
| Pinkovskiy and Sala-i-Martin (2009) | 1970–2006 | 191 | PovcalNet |
| Chen and Ravallion (2010) | 1981–2005 | 115 | WIID, PWT |

1. Countries for which data is imputed are not included.
2. PWT: Penn World Tables; WDR: World Development Report; WIID: UNU-WIDER World Income Inequality Database.

Two recent studies on global poverty—Chen and Ravallion (2010) and Pinkovskiy and Sala-i-Martin (2009)—present remarkably different estimates of global poverty due to different methodological approaches. As summarized in Table 2, key differences include the scope of the analysis (developing world vs. world) and the fact that Chen and Ravallion (2010) estimate consumption poverty whereas Pinkovskiy and Sala-i-Martin (2009) focus on income poverty. The relative distributions in Chen and Ravallion (2010) are scaled with mean consumption levels from HS, whereas Pinkovskiy and Sala-i-Martin (2009) scale them with NAS per capita income (GDP). Finally, Chen and Ravallion (2010) use a mix of individual records and grouped data and estimate a parametric Lorenz curve, while Pinkovskiy and Sala-i-Martin (2009) rely solely on grouped data and estimate the distribution employing the lognormal parameterization.

Thus, global poverty estimates in the literature not only differ in their use of HS or NAS as sources of data, but also in terms of coverage, type of data, choice of poverty lines, and estimation technique. Inherently estimates of global poverty from different studies are not comparable. In order to resolve this issue, we undertake a sensitivity analysis of global poverty estimates to two crucial choices, namely, the choice between HS and NAS as the source of data on well-being, and that between different estimation methods of the income distribution.

**Table 2 Methodological differences between recent global poverty studies**

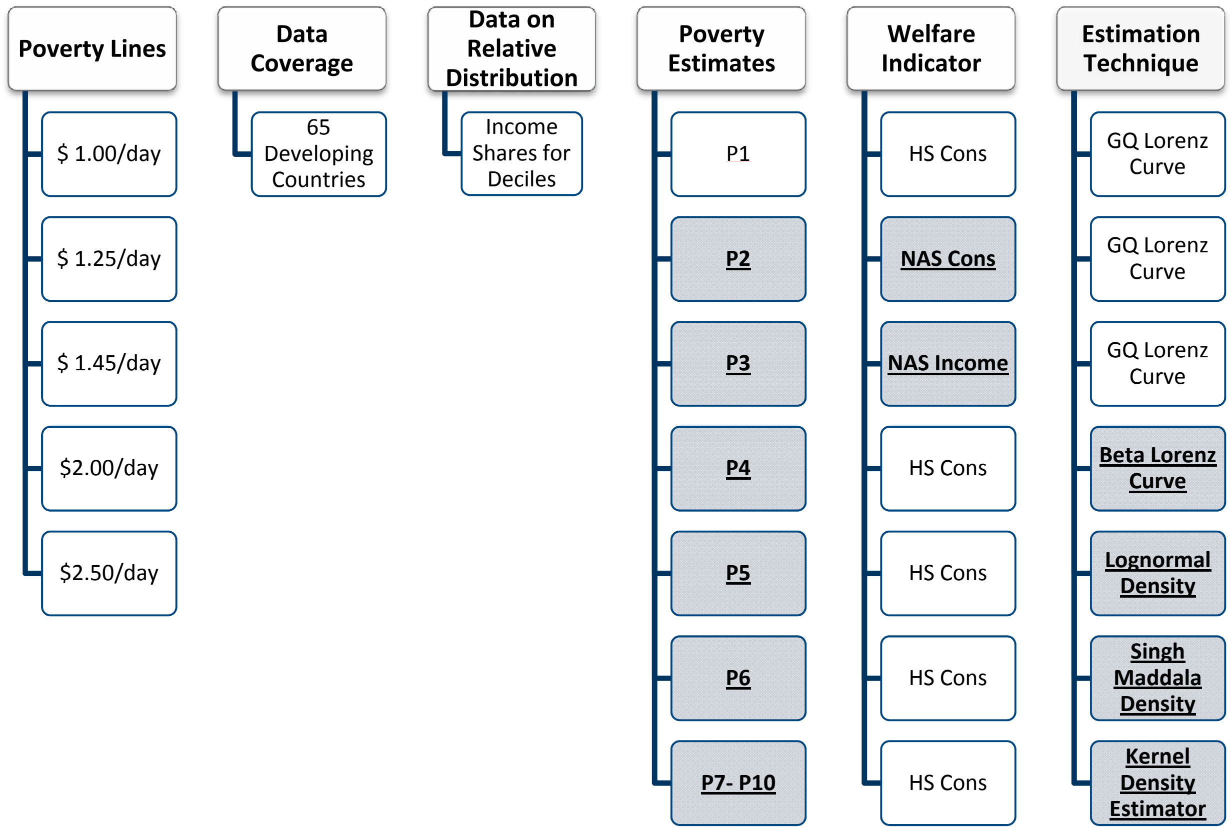
| Methodological choice | Chen and Ravallion (2010) | Pinkovskiy and Sala-i-Martin (2009) |
|---|---|---|
| Type of countries | Developing countries | Developed and developing countries |
| No. of countries | 115 | 191 |
| No. of surveys | 675 | 1,069 |
| Source of data | HS[1] | NAS |
| Type of data | Unit and grouped data | Grouped data |
| Welfare metric | Consumption | Income |
| Poverty line in 2005 PPP | \$1.25/day to \$2.5/day | \$1/day to \$10/day |
| Estimation technique | Lorenz curves (GQ) | Density functions (Log-normal, Gamma, Weibull) |

1. Adjusted NAS data is used when HS data is not available.

## III. Sensitivity Analysis

In this section we explain how we obtain poverty estimates in the sensitivity analysis and describe the data upon which these estimates are based. Figure 2 shows a schematic representation of the sensitivity exercise. The first row in the figure shows the method by which the benchmark poverty level is estimated. The shaded boxes show the different parameters chosen to estimate poverty in the sensitivity exercise.

**Figure 2 Schematic representation of the sensitivity analysis**




Notes: The grey-shaded boxes show parameters that were varied in the sensitivity analysis relative to the benchmark poverty estimate $P_1$.

## A. Notation

The poor are those individuals whose income is less than (or equal to) an income threshold called the poverty line. A broad class of poverty measures such as the Foster-Greer-Thorbecke (1984) poverty indices is then completely determined by three factors: the poverty line, the mean income/consumption level, and the relative distribution of income. The poverty level $P_1$ in a country can be expressed as:

$$P_1 = P(z, \bar{C}_{HS}, L_1(D))$$

where $z$ denotes the global poverty line, $\bar{C}_{HS}$ denotes mean consumption from household surveys, and $L_1$ denotes the GQ Lorenz curve which is estimated using data on income shares by decile from household surveys ($D$ is a $10 \times 1$ vector).[7] Thus the benchmark poverty

[7] Poverty rates are estimated for each country in the sample. Global poverty estimates are obtained by aggregating the number of poor in the sample.

estimate $P_1$ is based entirely on HS data and is estimated by largely replicating the World Bank methodology.

Keeping all other parameters fixed, we first test how poverty estimates vary when mean consumption from HS ($\bar{C}_{HS}$) is replaced by mean consumption from NAS ($\bar{C}_{NAS}$) and mean income from NAS ($\bar{I}_{NAS}$). The corresponding poverty estimates $P_2$ and $P_3$ are given by:

$$P_2 = P(z, \bar{C}_{NAS}, L_1(D))$$
$$P_3 = P(z, \bar{I}_{NAS}, L_1(D))$$

Unlike different poverty estimates available in the literature, $P_1$, $P_2$ and $P_3$ are fully comparable with one another. They are computed by applying the same statistical technique—the GQ Lorenz curve ($L_1$)—on the same distributional data ($D$) and differ only in terms of the means ($\bar{C}_{HS}, \bar{C}_{NAS}, \bar{I}_{NAS}$) used to scale the distribution.

Second, we analyze how the benchmark poverty $P_1$ varies when we use the same poverty line, same consumption mean ($\bar{C}_{HS}$), but estimate the distribution using different statistical methods.[8] Thus we estimate:

$$P_4 = P(z, \bar{C}_{HS}, L_2(D))$$

by fitting a Beta Lorenz curve ($L_2$) instead of the GQ Lorenz curve ($L_1$), and poverty rates

$$P_5 = P(z, \bar{C}_{HS}, F_1(D))$$
$$P_6 = P(z, \bar{C}_{HS}, F_2(D))$$

by estimating income density using respectively the lognormal ($F_1$) and the Singh-Maddala ($F_2$) functional forms. In addition to these parametric specifications, we also estimate poverty rates by fitting nonparametric kernel density functions ($K$) with different bandwidths. The bandwidth is the parameter that controls the smoothness of the estimated distribution. We obtain poverty rates:

$$P_7 = P(z, \bar{C}_{HS}, K_1(D))$$
$$P_8 = P(z, \bar{C}_{HS}, K_2(D))$$
$$P_9 = P(z, \bar{C}_{HS}, K_3(D))$$

[8] See the Appendix for details on the statistical methods.

$$P_{10} = P(z, \bar{C}_{HS}, K_4(D))$$

Poverty estimates $P_1$ ,$P_4$, $P_5$, $P_6$, $P_7$, $P_8$, $P_9$ and $P_{10}$ are directly comparable as they are based entirely on HS data and only differ in terms of the method employed to estimate the income distribution.

## B. Data

The sensitivity analysis is conducted by estimating poverty levels (discussed above) in 1995 and in 2005—the latest year for which data is available for a large number of countries.[9] Our sample includes 65 developing countries and covers more than 70 percent of the total world population (see Table 3). Relative distributions (*D*) for population deciles are obtained from the World Bank's PovcalNet database.[10] These are scaled alternately to mean consumption from surveys ($\bar{C}_{HS}$) also taken from PovcalNet, or mean consumption from NAS ($\bar{C}_{NAS}$) and mean income from NAS ($\bar{I}_{NAS}$) from the Penn World Tables Mark 6.3 (Heston, Summers, and Aten, 2009). Mean consumption/income values are expressed in 2005 PPP dollars.

We treat the $1/day poverty line as the lowest cutoff and estimate poverty by gradually increasing the poverty line to $1.25, $1.45, $2 and $2.50/day (all expressed in 2005 PPP dollars). The rationale for using multiple poverty lines is to assess robustness to small changes in the international poverty line, with the range $1–$2.5/day representing roughly a 95 percent confidence interval for the $1.25/day cutoff (Chen and Ravallion, 2010). Poverty is computed as the absolute headcount (or number of global poor) as well as the poverty headcount ratio (or poverty rate), which is the ratio of the number of poor to the total population in the countries included in the sample.

[9] For countries with no distributional data in 1995 and/or 2005, we use data from adjacent years, 1993–1997 and 2003–2007 (see Table 3).

[10] PovcalNet publishes survey data on consumption and/or on income shares in a country, depending on the nature of the underlying survey. Empirically, we find no systematic difference between the income and consumption shares available in the PovcalNet database hence we use the data without further adjustment and refer to them as "income shares" throughout the paper.

**Table 3 Country-years included in the sensitivity analysis**

| Country | Initial year | Final year | Country | Initial year | Final year |
|---|---|---|---|---|---|
| Albania | 1997 | 2005 | Kyrgyz Republic | 1993 | 2004 |
| Argentina | 1996 | 2005 | Latvia | 1995 | 2004 |
| Armenia | 1996 | 2003 | Lithuania | 1996 | 2004 |
| Azerbaijan | 1995 | 2005 | Madagascar | 1997 | 2005 |
| Bangladesh | 1995 | 2005 | Malawi | 1997 | 2004 |
| Belarus | 1995 | 2005 | Malaysia | 1995 | 2004 |
| Bolivia | 1997 | 2005 | Mali | 1994 | 2006 |
| Brazil | 1995 | 2005 | Mexico | 1995 | 2006 |
| Bulgaria | 1995 | 2003 | Moldova, Republic | 1997 | 2004 |
| Burkina Faso | 1994 | 2003 | Mongolia | 1995 | 2005 |
| Cambodia | 1994 | 2004 | Nepal | 1995 | 2003 |
| Central African Republic | 1993 | 2003 | Nicaragua | 1993 | 2005 |
| Chile | 1996 | 2006 | Niger | 1994 | 2005 |
| China[1] | 1995 | 2005 | Nigeria | 1996 | 2004 |
| Colombia | 1995 | 2006 | Pakistan | 1996 | 2004 |
| Costa Rica | 1996 | 2005 | Panama | 1995 | 2006 |
| Dominican Republic | 1996 | 2005 | Paraguay | 1995 | 2005 |
| Ecuador | 1994 | 2005 | Peru | 1996 | 2005 |
| Egypt | 1996 | 2004 | Philippines | 1997 | 2006 |
| El Salvador | 1995 | 2005 | Poland | 1996 | 2005 |
| Estonia | 1995 | 2004 | Romania | 1994 | 2005 |
| Ethiopia | 1995 | 2005 | Russian Federation | 1996 | 2005 |
| Georgia | 1996 | 2005 | Senegal | 1994 | 2005 |
| Guinea | 1994 | 2003 | Slovenia | 1993 | 2004 |
| Honduras | 1997 | 2005 | Thailand | 1996 | 2004 |
| Hungary | 1993 | 2004 | Turkey | 1994 | 2005 |
| India[1] | 1999 | 2005 | Uganda | 1996 | 2005 |
| Indonesia[1] | 1996 | 2005 | Ukraine | 1996 | 2005 |
| Iran | 1994 | 2005 | Uruguay | 1996 | 2005 |
| Jamaica | 1996 | 2004 | Venezuela, RB | 1995 | 2005 |
| Jordan | 1997 | 2006 | Vietnam | 1993 | 2006 |
| Kazakhstan | 1996 | 2003 | Zambia | 1996 | 2004 |
| Kenya | 1997 | 2005 | | | |

Source: WDI and the UNU-WIDER WIID for China, India, and Indonesia; PovcalNet for remaining countries.

# IV. Results

## A. Household Surveys vs. National Accounts Statistics

Household surveys are typically organized by national statistical agencies. These surveys collect information from sampled households on consumption expenditures and/or personal disposable income. As a result, HS-based consumption may suffer from flaws in survey design, lack of representativeness, recall bias, underreporting among the poor, and poor response rates among the wealthy.[11] National Accounts Statistics-based private consumption expenditure is computed by subtracting net exports, investment, and government expenditure from national income. Although in principle preparing NAS according to the UN system of National Accounts should be standard exercise, in practice there is a great deal of heterogeneity as countries make ad-hoc adjustments to the data.

HS-based ($\bar{C}_{HS}$) and NAS-based ($\bar{C}_{NAS}$) consumption differ both in level and in growth rates. $\bar{C}_{NAS}$ is typically higher than $\bar{C}_{HS}$ since it includes imputed rent on home-owners, imputed value of non-marketed items such as gifts, food produced and consumed at home, and consumption of non-profit organizations. $\bar{C}_{NAS}$ also grows faster than $\bar{C}_{HS}$ because it includes goods and services that are rarely consumed by the poor and because richer households are less likely to participate in surveys. Pure measurement error, differences in coverage, the presence of an informal sector, and differences in consumption deflators, cause further discrepancies. Similar considerations arise when income poverty is estimated using mean income from NAS ($\bar{I}_{NAS}$) rather than from HS. While differences between HS and NAS data have been analyzed in detail in the literature (Ravallion, 2003; Deaton, 2005) none of the existing studies have assessed how global poverty rates vary systematically using HS vs. NAS income and consumption. An exception is Bourguignon (2005) who employed a lognormal approximation of income distribution to assess the bias in poverty estimates by assuming different correlation coefficients between HS and NAS consumption.

In Table 4 we report summary statistics for $\bar{C}_{HS}$, $\bar{C}_{NAS}$ and $\bar{I}_{NAS}$ for all the countries in our sample. As noted in Deaton (2005), $\bar{C}_{HS}$ is typically lower than $\bar{C}_{NAS}$ and $\bar{I}_{NAS}$ is the highest of the three. The difference between the estimates has increased over time: while $\bar{C}_{NAS}$ was larger than $\bar{C}_{HS}$ by a factor 1.6 (or 1.9 for the unweighted sample) in 1995, this increased to 1.8 (or 2.3 for the unweighted sample) by 2005. The level difference between $\bar{C}_{HS}$ and $\bar{I}_{NAS}$ is even higher. Furthermore, $\bar{C}_{HS}$ registered the lowest increase of the three

[11] See Deaton and Grosh (2000) for problems with survey designs, Deaton and Kozel (2005) for recall bias, and Mistiaen and Ravallion (2003) for underreporting issues.

aggregates, with an average annual growth rate of 0.9 percent over the period, compared to 3.1 percent for $\bar{C}_{NAS}$ and 3.8 percent for $\bar{I}_{NAS}$.

**Table 4 Summary statistics for household surveys and national accounts means**

| Welfare Indicators | Max | Min | Un-weighted Mean | Un-weighted Std. Dev. | Population Weighted Mean | Population Weighted Std. Dev. |
|---|---|---|---|---|---|---|
| | | | **1995** | | | |
| $\bar{C}_{HS}$ | 6,668 | 287 | 1,922 | 1,350 | 1,222 | 998 |
| $\bar{C}_{NAS}$ | 8,205 | 625 | 3,095 | 1,879 | 2,256 | 1,421 |
| $\bar{I}_{NAS}$ | 13,436 | 791 | 4,957 | 3,431 | 3,877 | 2,377 |
| | | | **2005** | | | |
| $\bar{C}_{HS}$ | 8,241 | 409 | 2,148 | 1,512 | 1,331 | 1,065 |
| $\bar{C}_{NAS}$ | 11,714 | 624 | 4,104 | 2,611 | 3,051 | 1,733 |
| $\bar{I}_{NAS}$ | 22,004 | 834 | 6,669 | 4,927 | 5,614 | 3,064 |

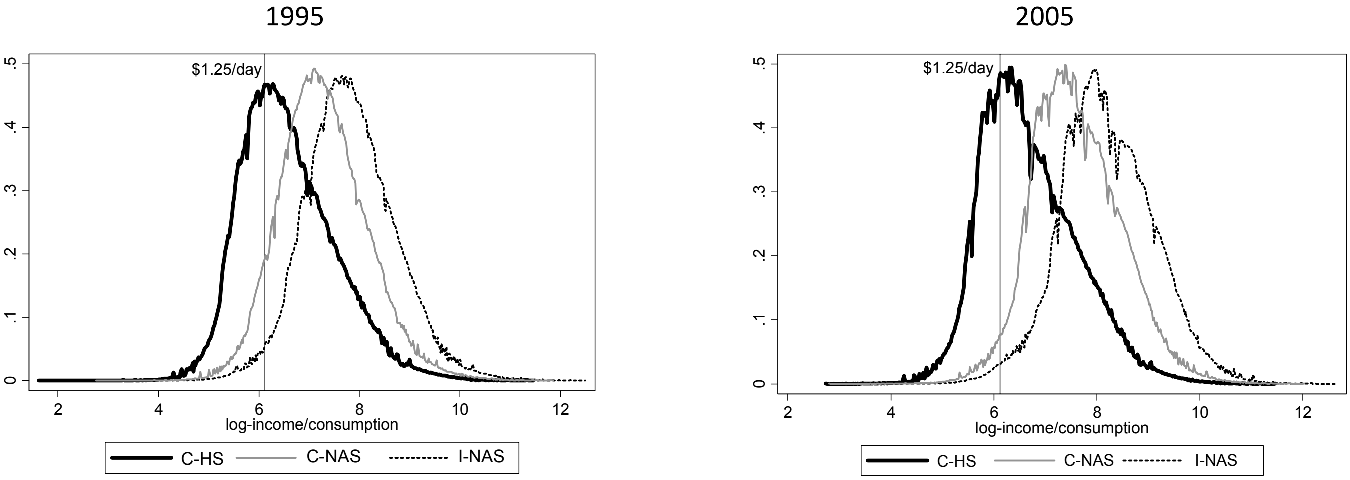
Source: PovcalNet for $\bar{C}_{HS}$ and PWT Mark 6.3 for $\bar{C}_{NAS}$ and $\bar{I}_{NAS}$. All figures in 2005 PPP dollars.

### B. Sensitivity to Household Surveys vs. National Accounts Statistics

We compute poverty estimates by alternately using $\bar{C}_{HS}$, $\bar{C}_{NAS}$ and $\bar{I}_{NAS}$ to scale national relative distributions.

Figure 3 shows the effect of these alternate anchors on the global income distribution. The global distribution is obtained by using our three welfare metrics ($\bar{C}_{HS}$, $\bar{C}_{NAS}$ and $\bar{I}_{NAS}$) to scale national relative distributions and aggregating up. Since the relative distributions are the same, the impact of the alternate anchors is to shift the global distribution along the horizontal axis without altering its shape. We hypothesize that the different estimates of mean income and consumption likely have a substantial level effect on the global poverty rate as suggested by the location of the \$1.25/day international poverty line on the income support (x-axis). Table 5 presents poverty estimates $P_1$ to $P_3$ computed by fitting the GQ Lorenz curve, which are comparable in every respect except that the relative distributions are anchored to different estimates of mean income or consumption (hence correspond to Figure 3).

**Figure 3 Global income distribution anchored to alternate estimates of mean income/consumption**




Source: Authors' estimations.

**Table 5 Sensitivity of global poverty estimates to survey vs. national accounts mean**

| | 1995 | | | 2005 | | | Percent Change | | |
|---|---|---|---|---|---|---|---|---|---|
| Poverty Lines $/day | $P_1$ | $P_2$ | $P_3$ | $P_1$ | $P_2$ | $P_3$ | $\Delta P_1$ | $\Delta P_2$ | $\Delta P_3$ |
| | | | | **Headcount Ratio (%)** | | | | | |
| 1.00 | 29.0 | 5.9 | 1.4 | 24.3 | 1.7 | 0.9 | -16 | -32 | -72 |
| 1.25 | 38.6 | 10.7 | 2.7 | 33.7 | 2.9 | 1.5 | -13 | -44 | -73 |
| 1.45 | 45.1 | 14.8 | 4.2 | 40.2 | 5.0 | 2.0 | -11 | -53 | -66 |
| 2.00 | 58.5 | 25.8 | 9.6 | 54.2 | 13.5 | 3.7 | -7 | -62 | -47 |
| 2.50 | 66.6 | 35.1 | 15.6 | 62.8 | 21.4 | 5.5 | -6 | -65 | -39 |
| | | | | **Absolute Headcount (millions)** | | | | | |
| 1.00 | 1,219 | 250 | 58 | 1,140 | 78 | 44 | -6 | -24 | -69 |
| 1.25 | 1,621 | 452 | 112 | 1,579 | 136 | 70 | -3 | -37 | -70 |
| 1.45 | 1,893 | 620 | 177 | 1,887 | 234 | 93 | 0 | -48 | -62 |
| 2.00 | 2,458 | 1,082 | 405 | 2,540 | 635 | 174 | 3 | -57 | -41 |
| 2.50 | 2,798 | 1,476 | 654 | 2,945 | 1,002 | 259 | 5 | -60 | -32 |

Source: Authors' calculations.

**Over Time**

Between 1995 and 2005, the $1/day headcount ratio declined by 16 percent when estimated as $P_1$ (from 29 to 24 percent), by 32 percent when estimated as $P_2$ (from 5.9 to 1.7 percent), and by 72 percent when estimated as $P_3$ (from 1.4 to 0.9 percent). The results confirm our prior that global poverty levels are higher when the welfare metric is HS consumption, lower when it is NAS consumption and least when it is per capita GDP. They also highlight the large extent to which the type of data used affects global poverty estimates. Poverty estimates vary significantly not only in terms of poverty headcount ratios, and correspondingly the total number of poor, but also in terms of the rate of decline in poverty.

**Across Poverty Lines**

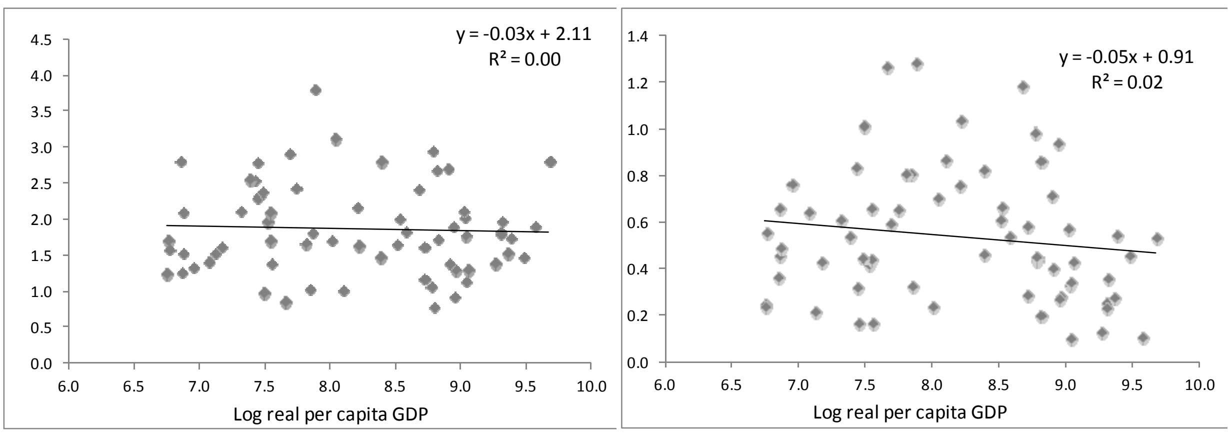
The estimates also vary systematically across different poverty lines: as expected, poverty rates increase with higher poverty lines. However, the rate of poverty reduction is lower for higher poverty lines (with the exception of $P_2$). While the falling trend of the headcount ratio is robust across the different thresholds, the number of poor has increased in some instances (for example, $P_1$ estimate for the $2/day and $2.5/ day poverty lines). The results are consistent with the increasing global poverty headcounts reported by Chen and Ravallion (2010) for the period 1981–2005. By contrast, $P_2$ and $P_3$ estimates consistently show a decline in the number of poor for all poverty lines, as shown in studies such as Pinkovskiy and Sala-i-Martin (2009), Sala-i-Martin (2006), and Bhalla (2002).

**Across Income Levels**

We explore whether country-level discrepancies in HS- and NAS-based poverty estimates vary with income level. Recall that $P_1$ and $P_2$ are estimated using the same method except that $P_1$ is based on $\bar{C}_{HS}$ whereas $P_2$ is based on $\bar{C}_{NAS}$. If richer countries were to measure HS consumption more accurately than poorer countries—for instance through better survey techniques and more comprehensive coverage—then the difference between HS and NAS-based poverty estimates would decrease with rising income. However, we do not find evidence to support this hypothesis. Figure 4 shows scatterplots of HS and NAS-based consumption and poverty estimates against log-per capita GDP levels. The regression line in the first panel has a near zero slope, which implies that the ratio $\bar{C}_{NAS}/\bar{C}_{HS}$ does not vary systematically with country income. The second panel plots the ratio of the corresponding poverty rates $P_2$ and $P_1$ against per capita GDP levels of countries. The ratio of the poverty rates, similar to the ratio of mean consumption, is not closer to 1 in higher income countries. Thus poverty estimates based on different consumption means vary significantly across countries, irrespective of their income levels.

**Figure 4 Ratios of consumption means and poverty estimates compared across income levels**

($\bar{C}_{NAS}/\bar{C}_{HS}$): Ratio of NAS to HS mean consumption ($P_2/P_1$): Ratio of NAS to HS-based headcount ratios




Note: Cross-country and time series data for 1995 and 2005 have been pooled. In the second plot the poverty headcount ratios correspond to the \$1.25/day poverty line. Per capita GDP is expressed in 2005 PPP dollars.

## C. Estimation Methods

The second sensitivity exercise concerns the choice of statistical method used to estimate the income distribution from grouped data. Several statistical methods—both parametric and nonparametric—can be used for this purpose. Parametric methods are applied, for instance, to estimate the Lorenz curve of income inequality. We estimate the GQ and the Beta Lorenz curves, which are commonly used in global poverty analysis and perform well in estimating poverty for a wide range of unimodal income distributions (Minoiu and Reddy, 2009).

Parametric methods are also applied to estimate the income density function. While many functional forms have been proposed in the literature, only a few have been applied to global poverty measurement. We focus on the lognormal and Singh-Maddala functional forms. The lognormal specification has traditionally been used in poverty estimation though other functional forms often provide a better fit for income distributions (Bandourian, MacDonald, and Turley, 2003; Bresson, 2009). Besides the lognormal, Pinkovskiy and Sala-i-Martin (2009) used the Gamma and the Weibull distributions to assess the robustness of poverty estimates. However Pinkovskiy and Sala-i-Martin (2009) did not report poverty estimates based on different income distributions, but only the correlation coefficients between different poverty rates. By contrast, we report actual estimates of global poverty corresponding to each statistical method considered.

In addition to these parametric techniques we also employ a nonparametric estimation method. The nonparametric method consists of applying a kernel density estimator on grouped data and has the advantage that no functional assumption needs to be made regarding the underlying data generating process. Sala-i-Martin (2006) estimated global poverty using a kernel density function to approximate national income distributions. Kernel density estimation requires specifying additional parameters such as the bandwidth—the smoothing parameter—which can have a large impact on the resulting estimate if applied to grouped data rather than to individual records (Minoiu and Reddy, 2008). Hence in the sensitivity analysis we use four different bandwidths for the kernel density estimator. The bandwidths are optimal in the sense that they minimize the approximate distance between the true and the estimated distribution (see Silverman, 1986).

## D. Sensitivity to Estimation Method

We undertake the sensitivity analysis of global poverty levels to estimation techniques by reverting back to the benchmark poverty level $P_1$ which was obtained by fitting a GQ Lorenz curve. Keeping all other methodological choices unchanged, we employ different statistical methods and assess the variance in poverty estimates. Poverty rate $P_4$ is based on Beta Lorenz curve, $P_5, P_6$ are based on the lognormal and Singh-Maddala density functions and $P_7$ to $P_{10}$ are based on nonparametric kernel densities (see Table 6).

**Across Methods**

Overall poverty estimates based on different estimation methods are highly correlated, an observation also noted by Pinkovskiy and Sala-i-Martin (2009). In particular, poverty estimates based on nonparametric methods ($P_7$ to $P_{10}$) vary to a lesser extent than do poverty estimates drawn from parametric methods ($P_1$, $P_4$ to $P_6$). Nevertheless, the observed variations in poverty estimates cannot be completely overlooked. For instance, poverty estimates for the $1/day poverty line range from 23.5 to 29 percent in 1995 and from 19.6 to 24.3 percent in 2005.

**Over Time**

As shown in Table 6, the falling trend in the global poverty rate is robust across estimation methods. Between 1995 and 2005, the rate of decline in the headcount ratio varied between 12 and 17 percent for the $1/day poverty line and between 5 and 9 percent for the $2/day poverty line. Compared to the headcount ratio, however, the trend in the number of poor is more ambiguous. Between 1995 and 2005, the absolute headcount according to the $1/day poverty line is estimated to have declined anywhere between 24 million and 83 million depending on the technique used. Only for the $1/day cutoff did the absolute headcount decline in all instances. By contrast, for the intermediate cutoffs ($1.25/day and $1.45/day) the number of poor increased or decreased depending on the estimation method. Finally, for the two highest poverty lines ($2/day and $2.5/day) the number of poor in fact increased over 1995–2005 irrespective of the estimation method used.

**Across Poverty Lines**

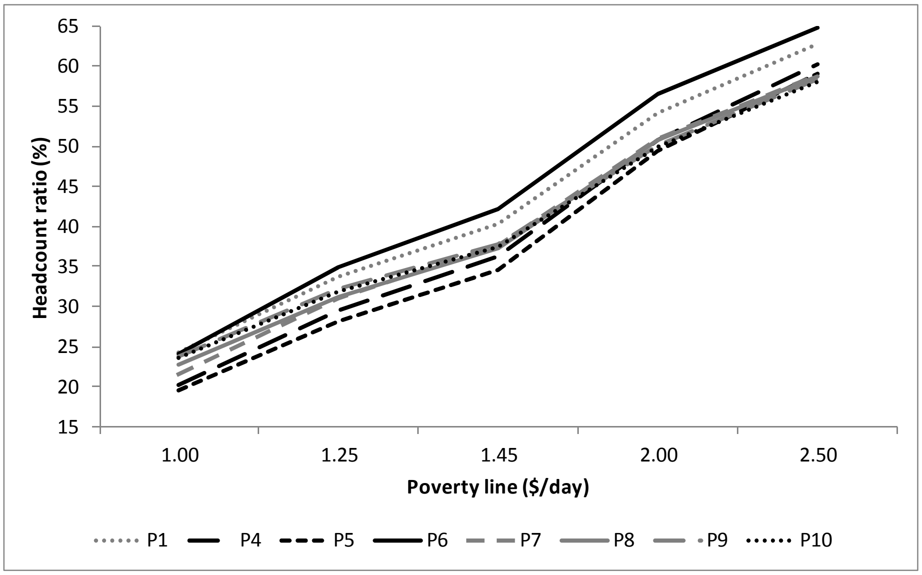
Figure 5 plots poverty rates corresponding to different statistical techniques and different poverty lines. We find that for most poverty lines, the Singh-Maddala functional form consistently provides higher estimates of poverty ($P_6$) whereas the Beta Lorenz curve ($P_4$) and the lognormal distribution ($P_5$) consistently yield lower estimates. A possible explanation is that the Beta parameterization provides a better fit at the higher end, while GQ does better at the low end of the Lorenz curve (Ravallion and Huppi, 1989). The lognormal parameterization leads to an underestimation of poverty relative to the well-performing GQ since it is too skewed to fit well real-world income distributions.

**Table 6 Sensitivity of global poverty to estimation method**

| Poverty Lines | Lorenz Curve: General Quadratic | Lorenz Curve: Beta | Parametric Density: Lognormal | Parametric Density: Singh-Maddala | Nonparametric Density: Silverman | Nonparametric Density: Normal scale | Nonparametric Density: DPI | Nonparametric Density: Over-smoothed |
|---|---|---|---|---|---|---|---|---|
| $/day | $P_1$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ | $P_8$ | $P_9$ | $P_{10}$ |
| **Headcount Ratio (%) 1995** | | | | | | | | |
| 1.00 | 29.0 | 24.4 | 23.5 | 27.7 | 26.0 | 26.8 | 27.7 | 26.9 |
| 1.25 | 38.6 | 34.0 | 32.8 | 38.6 | 35.3 | 35.1 | 36.0 | 36.0 |
| 1.45 | 45.1 | 40.8 | 39.4 | 45.6 | 41.4 | 41.2 | 41.7 | 41.7 |
| 2.00 | 58.5 | 55.3 | 54.1 | 59.5 | 54.7 | 54.2 | 54.3 | 54.0 |
| 2.50 | 66.6 | 64.3 | 63.4 | 67.7 | 62.9 | 62.1 | 61.9 | 61.8 |
| **Headcount Ratio (%) 2005** | | | | | | | | |
| 1.00 | 24.3 | 20.2 | 19.6 | 24.1 | 21.6 | 22.8 | 23.7 | 23.6 |
| 1.25 | 33.7 | 29.6 | 28.2 | 34.9 | 31.0 | 31.2 | 32.2 | 32.0 |
| 1.45 | 40.2 | 36.2 | 34.6 | 42.1 | 37.6 | 37.3 | 37.7 | 37.4 |
| 2.00 | 54.2 | 50.8 | 49.3 | 56.4 | 51.0 | 50.8 | 50.2 | 49.9 |
| 2.50 | 62.8 | 60.3 | 59.1 | 64.7 | 58.9 | 58.7 | 58.4 | 58.1 |
| **Absolute Headcount (millions) 1995** | | | | | | | | |
| 1.00 | 1,219 | 1,024 | 988 | 1,165 | 1,094 | 1,127 | 1,164 | 1,130 |
| 1.25 | 1,621 | 1,430 | 1,376 | 1,619 | 1,481 | 1,475 | 1,514 | 1,510 |
| 1.45 | 1,893 | 1,714 | 1,656 | 1,915 | 1,740 | 1,731 | 1,752 | 1,750 |
| 2.00 | 2,458 | 2,321 | 2,272 | 2,499 | 2,299 | 2,275 | 2,280 | 2,268 |
| 2.50 | 2,798 | 2,701 | 2,665 | 2,843 | 2,642 | 2,607 | 2,598 | 2,596 |
| **Absolute Headcount (millions) 2005** | | | | | | | | |
| 1.00 | 1,140 | 948 | 919 | 1,129 | 1,011 | 1,068 | 1,114 | 1,106 |
| 1.25 | 1,579 | 1,387 | 1,323 | 1,635 | 1,453 | 1,464 | 1,509 | 1,499 |
| 1.45 | 1,887 | 1,698 | 1,624 | 1,976 | 1,766 | 1,751 | 1,770 | 1,754 |
| 2.00 | 2,540 | 2,384 | 2,315 | 2,647 | 2,391 | 2,382 | 2,353 | 2,342 |
| 2.50 | 2,945 | 2,828 | 2,770 | 3,035 | 2,761 | 2,755 | 2,738 | 2,724 |
| | $\Delta P_1$ | $\Delta P_4$ | $\Delta P_5$ | $\Delta P_6$ | $\Delta P_7$ | $\Delta P_8$ | $\Delta P_9$ | $\Delta P_{10}$ |
| **Percent Change in the Headcount Ratio 1995-2005** | | | | | | | | |
| 1.00 | -16 | -17 | -17 | -13 | -17 | -15 | -14 | -12 |
| 1.25 | -13 | -13 | -14 | -10 | -12 | -11 | -11 | -11 |
| 1.45 | -11 | -11 | -12 | -8 | -9 | -9 | -10 | -10 |
| 2.00 | -7 | -8 | -9 | -5 | -7 | -6 | -8 | -8 |
| 2.50 | -6 | -6 | -7 | -4 | -6 | -5 | -6 | -6 |
| **Percent Change in the Absolute Headcount 1995-2005** | | | | | | | | |
| 1.00 | -79 | -76 | -69 | -36 | -83 | -59 | -50 | -24 |
| 1.25 | -42 | -43 | -53 | 16 | -29 | -12 | -5 | -11 |
| 1.45 | -6 | -16 | -32 | 61 | 26 | 20 | 18 | 4 |
| 2.00 | 82 | 63 | 43 | 148 | 92 | 107 | 72 | 74 |
| 2.50 | 147 | 127 | 106 | 192 | 118 | 147 | 139 | 129 |

Source: Authors' calculations.

**Figure 5 Global poverty rates in 2005 estimated using different statistical methods**




Note: Based on poverty estimates shown in Table 6.

## V. CONCLUSIONS

Over the past decades, global poverty monitoring has gained significance in international policy-making, more so with the adoption of the Millennium Development Goals. However, measuring global poverty has proved to be a difficult exercise both conceptually and empirically. Estimates of global poverty in the literature vary substantially, partly due to the diversity of assumptions made by researchers. Inherently global poverty estimates in the literature are not comparable since it is impossible to isolate and assess separately the relative importance of each such assumption. In this paper we conducted a novel sensitivity analysis by proposing a step-by-step approach to assess the relative importance of different assumptions for global poverty estimates.

We have assessed the sensitivity of global poverty estimates in relation to two crucial choices, namely that between household survey and national accounts estimates of income or consumption, and that of estimation method of the income distribution. Our key finding is that poverty estimates vary markedly when they are based alternatively on data from household surveys versus national accounts. Although the decline in the global poverty rate between 1995 and 2005 is found to be robust across methodological approaches, the number of poor and the rate of poverty reduction differ significantly depending on the data source used. It is reassuring that global poverty rates vary to a lesser extent when estimated with different statistical methods.

The results of our sensitivity analysis suggest that assessing robustness to methodological choices is an important step in global poverty measurement. More broadly, our findings suggest that the debate on global poverty would benefit from efforts to improve data collection practices across countries and to compile individual records from surveys into public databases. Such improvements would increase confidence in estimates of global poverty.

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## APPENDIX ON STATISTICAL METHODS

Let $x$ denote individual income, $f(x)$ the income density, $F(x)$ the cumulative density function (c.d.f.) and $\mu$ the mean income level in a country.

### Lorenz Curve Estimation

The Lorenz curve is defined as the relationship between the cumulative proportion of the population and the cumulative proportion of income received when the population is arranged in an ascending order of income. The Lorenz curve $L(p) = \frac{1}{\mu}\int_0^x xf(x)dx$ gives the share of the bottom $p$ percent of the population in total income, where $p = F(x) = \int_0^x f(x)dx$.

The poverty headcount ratio can be derived from the Lorenz curve by finding the point $p$ where the slope of the Lorenz curve is equal to the ratio $z/\mu$, where $z$ denotes the poverty line. We estimate a Generalized Quadratic (GQ) Lorenz curve given by: $L(1-L) = a(p^2 - L) + bL(p-1) + c(p-L)$ where $a$, $b$, and $c$ are unknown parameters estimated by Ordinary Least Squares (OLS) regression on grouped data. The Beta Lorenz curve is given by: $\log(p-L) = \log(\theta) + \gamma\log(p) + \delta\log(1-p)$ where $\theta$, $\gamma$ and $\delta$ are unknown parameters also estimated through OLS regression on the grouped data. The Beta specification requires numerical methods to compute poverty indicators.

### Parametric Density Estimation

In addition to estimating the Lorenz curve of income inequality, we estimate income distributions by specifying parametric functions. The lognormal function assumes that log-incomes are normally distributed with mean $\mu$ and variance $\sigma^2$. The c.d.f. of the two-parameter lognormal distribution is given by $F(x) = \Phi\left(\frac{\log(x) - \mu}{\sigma}\right)$, where $\Phi$ denotes the c.d.f. for the standard normal function. The mean $\mu$ is assumed to be equal to 1 while the variance is estimated using the procedure outlined in Shorrocks and Wan (2008). The c.d.f.

for the three-parameter Singh-Maddala distribution takes the form: $F(x) = 1 - \left(1 + \left(\frac{x}{\kappa}\right)^{\tau}\right)^{-\lambda}$ with parameters $\kappa, \tau, \lambda$. The poverty headcount ratio is estimated as the area in the lower tail of the c.d.f, whose parameters are estimated using maximum likelihood.

**Nonparametric Density Estimation**

Nonparametric methods impose no functional assumptions about the underlying data generating process. The standard kernel density estimator $\hat{f}(x)$ of the unknown (income) density $f(x)$ is given by $\hat{f}(x) = \frac{1}{Nh}\sum_{i=1}^{N} k\left(\frac{x - x_i}{h}\right)$ where $h$ is the bandwidth or smoothing parameter, $k(\cdot)$ is the weighting function or kernel and $i=1, \ldots N$ indexes income levels. We estimate the kernel density at 100 log-incomes. Since the choice of kernel function does not affect the poverty estimates significantly (Minoiu and Reddy, 2008), the standard Gaussian kernel is used. We choose four data-driven bandwidths, namely, Silverman's bandwidth, the Normal Scale bandwidth, and the Over-smoothed bandwidth—which assume that the underlying distribution of log-incomes is normal; and the two-step direct-plug-in (DPI) bandwidth (Wand and Jones, 2005). All parametric estimations are performed using the STATA package DASP Version 2.1 (Abdelkrim and Duclos, 2007) and nonparametric estimations are performed using the STATA *kdens* routine (Jann, 2005) explained in detail in Jann (2007).