

ISERP

Working Paper 07-02

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CAMELIA MINOIU

DEPARTMENT OF ECONOMICS
COLUMBIA UNIVERSITY

SANJAY REDDY

DEPARTMENT OF ECONOMICS, BARNARD COLLEGE
COLUMBIA UNIVERSITY



COLUMBIA UNIVERSITY IN THE CITY OF NEW YORK

JANUARY 2007

INSTITUTE FOR SOCIAL AND ECONOMIC RESEARCH AND POLICY

PIONEERING SOCIAL SCIENCE RESEARCH AND SHAPING PUBLIC POLICY

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Camelia Minoiu²

Department of Economics
Columbia University

Sanjay Reddy³

Department of Economics
Barnard College

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January 2007

9,328 Words

9 Tables

4 Figures

¹ We are grateful for the support of the Bureau of Development Policy and the International Poverty Centre of the United Nations Development Program. We would like to thank Terry McKinley for facilitating that support. We would also like to thank Shaohua Chen, Gaurav Datt, and Martin Ravallion for helpful comments and Sergey Kivalov for assisting us with software development. We would like to thank Catherine Choi and Prabhjot Kaur for research assistance.

² Dept. of Economics and Institute for Social and Economic Research and Policy, Columbia University. Email: cm2036@columbia.edu Tel. 212-854-6385, Fax. 212-854-7998.

³ Dept. of Economics, Barnard College, Columbia University and Institute for Social and Economic Research and Policy, Columbia University. Email: sr793@columbia.edu. Tel. 212-854-3790, Fax. 212-854-8947.

⁴ Updated versions of this paper will be made available on www.columbia.edu/~sr793/povcalnote.pdf

Abstract

The estimation of poverty and inequality often requires the use of grouped data as complete household surveys are neither always available to researchers nor easy to analyze. In this study we assess the performance of two functional forms for the Lorenz curve proposed by Kakwani (1980) and Villasenor and Arnold (1989). The methods are implemented using the computational tool POVCAL, developed and distributed by the World Bank. To identify biases associated with this method of estimating the two Lorenz curve functional forms, we analyze unit data from several household surveys and a wide range of theoretical distributions. We find that poverty and inequality is better estimated when the data is generated from unimodal distributions than when it is drawn from multimodal distributions. For unimodal distributions, the biases in the estimation of poverty measures are rarely larger than one percentage point. Inequality (measured by the Gini coefficient) is well estimated in most cases considered. Neither of the two Lorenz curve estimation methods provides consistently superior performance, and performance does not always improve with the number of data points analyzed.

Keywords: grouped data, Lorenz curve, poverty, inequality, income distribution, parametric estimation, POVCAL

JEL Classifications: C13, C14, C15, C16, D31, D63, I32

Wordcount: 9,328

| 1 | INTRODUCTION

The estimation of poverty and inequality often requires the use of grouped data (i.e. data concerning the mean incomes, or other advantages¹, of population quantiles such as quintiles or deciles) as complete household surveys are not always available to researchers. Moreover, the analysis of complete household surveys is often labour and time-intensive. Some applied research, such as attempts to estimate regional and global poverty, have extensively used estimates derived from grouped data for both of these reasons.² Grouped data has provided the sole source of information on income distributions of large countries (such as China) which play a crucial role in determining our picture of the extent and trend of world poverty and inequality.³ Further, grouped data often provides the *only* source of historical data (survey data from the past may no longer be available but summary statistics from these surveys may have been published) and thus plays an important role in the estimation of long run trends.⁴ Data on the size distribution of firms is also often available only in grouped form.

Several methods have been proposed in the literature to obtain estimates of poverty, inequality, the density function or the Lorenz curve from grouped data: a first approach relies on the *parametric* estimation of the density function and/or that of the Lorenz curve. A second approach involves *nonparametric* (e.g. kernel density) estimation of the income density. It has recently been employed by Sala-i-Martin (2002a, 2002b, 2006) and other researchers.⁵

In this study we analyze the performance of the ready-to-use software POVCAL, developed and distributed by the World Bank, which is widely used to implement one of these methods – parametric estimation of the Lorenz curve.⁶ POVCAL is used to produce the national poverty estimates used in the construction of global poverty assessments when underlying household surveys are not available but grouped data is available (see, e.g., Bhalla 2002, Chen and Ravallion 2001 and 2004, and Pritchett 2006 in regard to global poverty estimates; Chen and Wang, 2001 and Chen and Ravallion, 2005 in regard to national poverty

¹ In what follows, we bear in mind that poverty and inequality analysis can be applied to distributions of consumption, income or other dimensions of personal advantage. However, without loss of generality we refer to income distributions throughout the paper.

² Quite apart from the lack of availability of surveys for all countries and all years, and the prohibitively large volume of data which needs to be analyzed, the exercise is further complicated by issues relating to the inter-country comparability of surveys and of poverty lines, which we do not address further here. For discussion of the issues involved, see e.g. Deaton (2005), Milanovic (2005), Chen and Ravallion (2004), Reddy and Pogge (2006), Pogge and Reddy (2006), and Reddy, Visaria and Asali (2006).

³ See, for example, Chen and Ravallion (2004) and Reddy and Minoiu (2006). China's State Statistics Bureau has not made the full household survey data it collects available to outside researchers.

⁴ See, e.g. Bourguignon and Morrison (2002) for a study heavily relying on such grouped data as the basis for historical comparisons.

⁵ For example, Ackland et al (2004), Dhongde (2005), and Fuentes (2005). Minoiu and Reddy (2006) provide an assessment of the kernel density estimation approach.

⁶ Some of the functions of the stand-alone software are built in to the PovcalNet website of the World Bank (<http://iresearch.worldbank.org/PovcalNet/jsp/index.jsp>), which allows users to obtain poverty estimates for any country in the period covered for a specified poverty line. The user can choose the PPPs to be applied if poverty is to be estimated relative to an international poverty line expressed in US\$. A set of PPPs is available as a default option.

estimates). A number of studies of the progress of specific countries and of the world towards the first Millennium Development Goal (halving severe poverty by the year 2015) have employed POVCAL (see, e.g., Woo et al, 2004 for such an assessment of poverty reduction in China and Karshenas, 2004 for such an assessment for the world and for specific regions).

POVCAL has been used in the construction and reporting of Gini coefficients in the UNU-WIDER World Income Inequality Database V.2.0a (2005) and the World Bank's Measuring Income Inequality Database (Deininger and Squire, 1996) and has thereby subsequently influenced a large number of cross-country econometric analyses that have employed these two databases.⁷ POVCAL is extensively used to estimate Lorenz curves and associated poverty and inequality estimates in both academic and operational work. For example, it has been widely used in the preparation of national poverty assessments⁸ and recommended to practitioners as a standard poverty assessment tool by various development agencies⁹.

The software fits a Lorenz curve from grouped data using two alternative parameterizations (Kakwani, 1980a and Villasenor and Arnold, 1989) and presents as output estimates of the Lorenz curve and of several poverty and inequality indicators. It estimates parameters for the two functional forms by transforming them into a linear form and using ordinary least squares regression. From this perspective, we are evaluating the use of the functional forms proposed in conjunction with a specific method used to identify best-fitting parameters (OLS regression) which could in principle also be changed (e.g. to maximum likelihood estimation). We seek to assess whether there are sizable or systematic biases in the estimated Lorenz curves and associated measures of poverty and inequality. To this end, we use (i) household survey data from four countries (China, Nicaragua, Tanzania and Vietnam), (ii) data drawn from several theoretical distributions (Weibull, Pareto, Log-normal and Generalized Beta II) with parameter values assigned on the basis of previous empirical estimates, and (iii) Monte Carlo simulations of surveys of a population with incomes distributed according to two distributions (the Dagum distribution and a multimodal distribution corresponding to the world inter-personal distribution of per capita income). We compare the Lorenz curve, poverty and inequality estimates obtained from POVCAL applied to grouped data with those obtained directly from the underlying distributions. Plots of all distributions used in the paper are presented in Figures 1 and 2 in the Appendix.

We find that POVCAL performs relatively well in estimating poverty and inequality from distributions that are unimodal. Larger biases were identified in the case of a multimodal distribution. Inequality (measured by the Gini coefficient) is accurately estimated in most cases considered. We also find that the biases of poverty and inequality estimates vary (albeit not systematically) with the number of datapoints analyzed, the interpolation method, the

⁷ See, e.g., Lundberg and Squire (2003), Banerjee and Duflo (2003), Milanovic (2002), Forbes (2000), Easterly (1999), and Deininger and Squire (1998). Furthermore, Son and Kakwani (2006), Belkacem and Limam (2004), and Figini and Santarelli (2006) produce their own estimates of inequality and poverty using POVCAL and employ them in cross-country econometric analyses.

⁸ A small sample of the studies which employ the software for national poverty assessment is the following: Ali and Elbadawi (2002) for Sudan, Asra (2000) for Indonesia, Belkacem (2001) for Algeria, Eele et al (2000) for Tanzania, Acharya (2004) for Nepal, Joeques et al (2000) for Pakistan.

⁹ See, for example, USAID (2004) and World Bank (2003).

nature of the underlying true distribution, the poverty line, and the indicator chosen for poverty assessment. We encountered a series of technical problems with the software when using certain distributions (in particular, multimodal and Pareto distributions).

The paper is structured as follows. Section 2 briefly discusses grouped data and previous assessments of the performance of various parametric Lorenz-curve fitting techniques. Our findings concerning biases in POVICAL's estimates in relation to their true (theoretical) or survey counterparts from underlying distributions are presented in Sections 3 and 4. Some conclusions are drawn in Section 5.

| 2 | PARAMETRIC ESTIMATION OF LORENZ CURVES USING POVCAL: THE APPROACH AND PREVIOUS ASSESSMENTS

The Lorenz curve is estimated by POVCAL from grouped data by regression analysis based on two alternative functional forms, each involving three parameters (see Datt 1998, p. 6). The Generalized Quadratic parameterization (henceforth, 'GQ') was proposed by Villasenor and Arnold (1989) while the Beta parameterization was proposed by Kakwani (1980a). The grouped data read by the program may take different forms - e.g. income shares of quantiles (income classes with common population size), mean incomes for quantiles, percentage of the population in given income intervals, etc.

For a user-specified poverty line, the output of the software includes: the poverty headcount ratio (FGT0), the poverty gap index (FGT1), the squared poverty gap (FGT2), and the elasticity of the aforementioned poverty measures with respect to the mean income (assuming a constant distribution). POVCAL also reports the Gini coefficient of inequality. Furthermore, it reports estimates of the Lorenz curve and produces graphs of the curve. Based on goodness-of-fit criteria (namely, minimization of the overall sum of squared fitted errors and the sum of squared fitted errors over the part of the Lorenz curve corresponding to proportions of the population beneath the headcount ratio, it determines which of the two parameterizations offers a better fit to the grouped data. Finally, the software reports on the consistency of the Lorenz curve estimate with the requirements for a valid Lorenz curve.¹⁰

Despite its widespread use, evidence on the accuracy of POVCAL's estimates is limited. One assessment of the performance of these two parameterizations is that by Ravallion and Huppi (1989). The authors used grouped data on household consumption from 50,000 randomly selected Indonesian households and compared estimates of the Lorenz curve obtained via three parametric functional forms - those associated with Villasenor and Arnold (1989), Kakwani and Podder (1976), and Kakwani (1980a) - with the estimates obtained directly from unit data from the survey. The parameterizations considered include the two incorporated into POVCAL. They found that the worst fit is provided by the two-parameter specification of Kakwani and Podder (1976), while the other two specifications give broadly similar results.¹¹ They also found that Villasenor and Arnold's parameterization provided a

¹⁰ The theoretical invalidity of the Kakwani (1980a) Beta functional form is noted by Ortega et al (1991). It can easily be shown algebraically that this functional form *always* violates conditions required for the validity of the Lorenz curve (in particular by implying a negative slope at the origin). The GQ parameterization gives rise to valid Lorenz curves only under certain conditions on its parameters. Villasenor and Arnold (1989) find that the estimated GQ Lorenz curve is sometimes invalid in empirical estimates. We also find this to be the case. The possibility of negative estimated income shares is inherent in the use of OLS regression as a method of estimating the parameters, since the linear specification cannot be applied in a manner that wholly rules out this possibility.

¹¹ Kakwani and Podder (1976) discuss the goodness of fit of their two-parameter specification. An empirical exercise which they undertake (using data from the 1967-68 Australian Survey of Consumer Expenditures and Finance) reveals underestimation of the mean income of the poorest 5 percent of the population, and overestimation of the mean income of the poorest 10 percent. Anand (1983), and Anand and Kanbur (1993a, 1993b) note that there are reasons in theory to doubt the satisfactoriness of Kakwani and Podder's (1976) proposed functional form for parametric estimation of the Lorenz curve. A related study is that by Dhongde (2004), who theoretically derives the small sample bias of Lorenz curve estimates associated with the earlier parameterization of Kakwani and Podder (1973).

better fit towards the high end of the income distribution (for higher quantiles), while Kakwani's 1980 parameterization did so for lower quantiles.

Using the 1967-1968 Australian Survey of Consumer Expenditure, Villasenor and Arnold (1989) assess the goodness of fit of the GQ functional form. The authors find that GQ is superior to three alternative parameterizations (those proposed by Kakwani and Podder (1976), Pakes (1981), and the classical Pareto distribution) based on the criterion of minimizing the sum of squared and absolute errors of the Lorenz curve estimates over the entire support. They also report that the greater the number of income quantiles, the better the fit. The authors judge the performance of their approach to fitting the Lorenz to be satisfactory for bimodal income distributions. However, the best fit of the Lorenz curve by the elliptical curves that they employ was achieved for unimodal distributions. Kakwani (1980a) assesses the goodness-of-fit of Lorenz curve estimates based on the Beta parameterization using the 1974 Australian Household Expenditure Survey. The coefficients of determination from the estimating regressions (not reported in the paper) are close to 0.99, while the estimated values of the Lorenz curve are found to be within two decimal places of the survey-based values.

More recently, Cheong (2002) undertook a comparison of alternative functional forms for parametric estimation of the Lorenz curve. The author assesses the performance of four parameterizations of the Lorenz curve (namely those proposed by Kakwani and Podder (1976), Rasche et al (1980), Kakwani (1980a) and Ortega et al (1991)) in estimating the Gini coefficient from U.S. income data in grouped form (for one hundred income classes). The Pareto Lorenz curve proposed by Rasche et al (1980) was suggested as an alternative to the approach of Kakwani and Podder (1976). The authors point out that the latter approach relies on functional forms which, in principle, always violate the conditions for a valid Lorenz curve. In a response, Kakwani (1980b) defended the parameterization on the grounds that it performed well empirically for a wide range of income distributions. In his study, Cheong (2002) found that Kakwani's Beta form provides as good a fit to the data as does that of Rasche et al.

While many Lorenz curve functional forms have been proposed in the literature¹², an exhaustive assessment of their performance is not the object of this study. The main reason for restricting our attention to Villasenor and Arnold (1989) and Kakwani (1980a) is that these two parameterizations are the most extensively used in applied work (and in particular, with a view to estimating national, regional and global poverty) due to their availability through the computational tool POVCAL.

¹² See also Gupta (1984), Basmann et al (1990), and Ogwang and Rao (1996).

| 3 | MONTE CARLO STUDIES

In this section, we describe the results of a Monte Carlo analysis of the interpolation techniques used by POVCAL. We use grouped data drawn from a flexible parametric distribution - the Dagum distribution¹³ - and from a multimodal distribution corresponding to the world inter-personal distribution of per-capita income. Bandourian et al (2002) provide evidence that the Dagum distribution provides the best fit to real income distributions in the family of *three parameter distributions*. As Jenkins and Cox (1999) note, the Dagum distribution provides a good fit to empirical income data relative to other parametric functional forms in large part because of its appropriateness for fitting skewed empirical distributions. The multimodal distribution that we use is the 2004 population-weighted world distribution of income, in which the individuals in each country are assigned the per capita PPP-adjusted GDP of that country. The two higher peaks of the distribution (occurring at lower income levels) correspond to population mass concentrated at the per capita incomes of China and India, while the lower peak (occurring at a higher income level) corresponds to the population mass of the rich nations (Figure 1).

From each hypothesized density, we draw 100 random samples of 1000 observations each.¹⁴ Quintile, decile and ventile means are then computed from each sample and entered into POVCAL. We do not consider cases beyond ventiles since in practice at most twenty datapoints are typically available to researchers (see, for example, the UNU-WIDER World Income Inequality Database V.2.0a, 2005). Furthermore, we use POVCAL to estimate poverty for multiple poverty lines in order to determine the accuracy of the two interpolation techniques at different points along the support of the Lorenz curve.¹⁵

1. Fitting the Lorenz Curve

We first assess the accuracy of POVCAL-based output by comparing estimates of the Lorenz curve from grouped data with those obtained from the hypothesized true distribution from which the samples are drawn. We assess the goodness of fit of the estimates along the entire curve (and up to a poverty headcount ratio of 20 percent) by computing the sum of squared errors (SSE) and the sum of absolute errors (SAE), as well as a measure of the average extent

¹³ The Dagum distribution has the following parameter values: $a = 2.742$, $b = 100,000$ and $c = 0.337$. These are the median parameter values from the reported best-fitting Dagum parameters for a series of 27 countries' income distribution in recent years (Bandourian, McDonald and Turley, 2002). The parameter values are closest to those fit by the authors for Russia's 1992 income distribution.

¹⁴ In the case of the multimodal distribution, we draw 100 random samples from a universe of almost 600,000 observations representing a model of the world's population in which each individual has been assigned the 2004 per capita income of the country in which they live. In the case of the Dagum distribution, we draw 100 random samples from a universe of one million observations. We restrict the number of draws to 100 due to the high volume of manual work involved in running POVCAL on these samples.

¹⁵ For the Dagum distribution, the poverty lines are set at the median times the following multiplicative factors: 1.33, 0.5, 0.33, and 0.25. For the multimodal distribution, the poverty lines are the \$1.08/day and \$2.15/day money-metric international poverty lines, 0.75 times the median (falling between the two modes of the log-income distribution) and 1.33 times the median of the distribution (falling to the right of the third mode of the log-income distribution).

to which POVCAL under- or overestimates the Lorenz curve at different points along the curve (expressed in percentage points). The results are reported in Tables 1-3.

Based on the goodness of fit statistics (Table 1), we note that a higher number of quantiles used in the analysis implies a lower SSE and SAE (for the GQ parameterization) but (surprisingly) the reverse is the case for the Beta parameterization. If the SSE and SAE are computed up to a headcount ratio of 20 percent (i.e. for the Lorenz curve truncated after the twenty percent of the population with lowest incomes), the Beta parameterization performs worse than the GQ method, except in the case of quintile data.

Average Lorenz curve estimates for population proportions up to 10 percent are reported in Table 2. These give a more fine-grained indication of the performance of POVCAL in the left tail of the income distribution. A series of interesting patterns arise: first, the GQ method leads to overestimation of the income share accruing to each population proportion toward the left side of the support. In contrast, the Beta parameterization yields *negative* average Lorenz curve estimates for the bottom population centiles, which renders the estimated Lorenz curve invalid. The software correctly reports on the invalidity of the Lorenz curve when negative income shares are predicted. To see how the parameterizations perform across the entire support, we report the average Lorenz curves estimates for each cumulative population decile (Table 3). It is apparent that the proportion of cumulative income possessed by a given cumulative proportion of the population is consistently overestimated. As a result, the actual Lorenz curve is dominated by the estimated Lorenz curve, which implies that distortions in the Lorenz curve arise along the entire support (Figure 3). It follows that any Lorenz-consistent measure of inequality would therefore register lower estimated than actual inequality. The magnitude of the biases is very similar regardless of the number of quantile means and the estimation method (GQ or Beta).

We repeated the exercise of estimating the Lorenz curve using grouped data from the notional multimodal distribution (Tables 4-6). Using the SAE criterion, the GQ functional form provides a worse fit when more quantile means are used, while with the Beta functional form, the SAE does not vary monotonically with the number of quantile means. Furthermore, both parameterizations give rise to negative estimated income shares for all (or some) population shares (Table 5). Table 6 indicates that both parameterizations lead to some degree of underestimation of the Lorenz curve (as opposed to results from the Dagum distribution). Figure 4 offers a visual representation of these findings by superimposing average Lorenz curve estimates for quintiles, deciles and ventiles, against their true counterparts. Since there is underestimation of cumulative income shares at some cumulative population shares, and overestimation at other shares, the estimated and actual Lorenz curves cross. It follows that whether the use of the estimated Lorenz curve will lead to a lower or higher value of a Lorenz-consistent inequality index than for the actual Lorenz curve is in principle dependent on the specific features of the index.

From this analysis, we conclude the following: (a) For the Dagum distribution, regardless of the number of quantile means used in the analysis, the GQ interpolation method provides a better overall fit of the Lorenz curve than the Beta interpolation method based on the SSE and SAE. For the multimodal distribution, the goodness-of-fit statistics sometimes vary non-monotonically with the number of datapoints and no one interpolation method is consistently superior. (b) For the Dagum distribution, unlike the GQ interpolation method,

the Beta interpolation method yields negative Lorenz curve estimates for population proportions below four percent. In contrast, for the multimodal distribution, the GQ interpolation method generate negative income shares up to the bottom 10 percent of the population, while the Beta interpolation method in general yields positive income shares. In both cases, POVCAL correctly reports the instances when the estimated Lorenz curve is invalid. (c) Both parametrizations are associated with an overestimation of income shares that accrue to population proportions along the support in the case of one distribution (Dagum) and often with an underestimation of income shares along the support in the case of the other distribution (multimodal). It is not possible to derive from his exercise any general conclusions concerning which of the approaches used to estimate the Lorenz curve is best.

2. Estimating Poverty and Inequality

In this sub-section, we use data from the Dagum distribution and the notional multimodal distribution to compare POVCAL-based estimates of poverty and inequality with their true counterparts. We report the results for poverty indicators in Table 7 (Dagum distribution) and Table 8 (multimodal distribution) and those for the Gini coefficient in Table 9. In each table, the bias is expressed in (average) percentage points of deviation from the true value.

Table 7 shows that for most of the poverty lines considered and for all poverty indicators, the average bias is rarely higher than one percentage point. However, when the data are generated by the the Dagum distribution, the interpolation is performed with the Beta method, and the poverty lines are low, then the bias is occasionally higher than one percentage point. For the Dagum distribution, therefore, the two parameterizations perform exceptionally well in estimating poverty. The GQ parameterization appears to slightly outperform the Beta parameterization. As we found previously, a higher number of datapoints is *not* associated with increased accuracy of poverty estimates. The magnitude of the biases, however, is quite small throughout.

The parameterizations perform less well when data is drawn from the multimodal distribution (Table 8). First, we often cannot report poverty biases for the \$2.15/day poverty line due to the frequency with which POVCAL shut down, failed to write to the output files, provided meaningless output (e.g., higher than one poverty headcount ratios) or generated infeasible bounds for the poverty lines. Examples of such technical problems encountered when running POVCAL are described in Box 1. The biases are thus computed across successful program runs. We notice the following patterns: first, the magnitude of the biases is often larger than it was for the Dagum distribution. Frequently, more datapoints are associated with larger biases. Furthermore, the sign of the biases changes from positive (for quintile data) to negative (decile and ventile data) as the number of data points increases and as the poverty line is increased. There are no stark differences in how each of the two parameterizations performs. In contrast, it is clear that the Gini coefficient is more accurately estimated when the Beta parameterization is used, regardless of the distribution to which it is applied (Table 9). Biases are extremely small when data is drawn from the Dagum distribution, but the estimates are off by up to 5 percentage points (Dagum) and 3.7 percentage points (multimodal) when quintile means are used as input data.

From these results, it is difficult to identify any regularities in the relationship between the size and sign of biases and the parametrization or the number of datapoints used, other than that the biases are larger when the true distribution is multimodal. As Villasenor and Arnold (1989) note in their assessment of the GQ parameterization (for an elliptical Lorenz curve), the functional form provides a good fit to data from the unimodal family of densities, but less so to data with bimodal histograms.

| 4 | DETERMINISTIC COMPARISONS

In this section we report on the accuracy of POVCAL in replicating features of underlying income distributions using data from actual representative household surveys and from selected theoretical distributions (with parameters chosen according to previous empirical estimates). We compare POVCAL's output based on grouped data with the values derived from analysis of unit data. We use surveys for China (1995 Chinese Household Income Project¹⁶), Tanzania (2000-01 Tanzanian Household Budget Survey), Nicaragua (1997-98 Nicaraguan Living Standards and Measurement Survey) and Vietnam (1998 Vietnam Living Standards Survey).

To cover a wider range of plausible income distributions, we also use unit data generated from theoretical distributions with parameter values that have been shown to provide a good fit to other countries' income distributions. For example, the Weibull distribution is the best fitting *two parameter distribution* for the countries examined (Bandourian et al, 2002). The parameters chosen for the Weibull distribution are those corresponding to United States' 1997 income distribution. The log-normal distribution has been widely used in income distribution studies (see, for example, the estimation of country income distributions by Babones, 2003). The parameters we use for the Weibull distribution correspond to Russia's 1995 income distribution (as estimated by Bandourian et al, 2002). The Generalized Beta II distribution is found by the same authors to provide the best fit from within the family of *four parameter distributions* to empirical income distribution data for a range of countries, and has also been used in other empirical literature on the estimation of income distributions (see e.g. Rao et al, 2004). The parameters we use for the Generalized Beta II distribution are based on the parametric estimation of Mexico's 1996 income distribution in Bandourian et al (2002).

The Pareto distribution has also been used in empirical studies of income distribution. In particular, it has been argued that it provides good estimates of the right tail of income distributions (see, e.g., Aoyama et al, 2000 for Japan and Clementi and Gallegati, 2005 for Italy). The parameters we use for the Pareto distribution are based on the parametric estimation of Italy's 2002 income distribution in Bandourian et al (2002). Each 'hypothetical' country with unit data drawn from these distributions contains one million (income) observations.

¹⁶ The 1995 Chinese Household Income Project, as well as the SAS codes for constructing measures of disposable rural and urban income, are publicly available through the Inter-University Consortium for Political and Social Research, 2000. We pooled the rural and urban surveys to obtain the income variable for the country, which represents per capita household income (with no adjustment for household composition). For a detailed description of this variable, see Appendix 5A in Reddy and Minoiu (2006).

The small-sample biases for selected poverty indicators and inequality are reported in Tables 10-12.¹⁷ These results indicate that for many distributions, the biases associated with the poverty indicators are very small: the magnitude of these biases is seldom larger than one percentage point (in either direction).¹⁸ Comparison between POVCAL's output and poverty estimates from the underlying survey data (Table 10) suggests that POVCAL generally performs well in estimating the poverty headcount ratio. For the log-normal distribution, the biases are larger for the Beta parameterization and the lowest poverty line considered (Table 11).

For China (Table 12), we note that the poverty headcount ratio is under-estimated by more than 2 percentage points for poverty lines lower than a quarter of the survey median (using the 1995 income survey from the China Household Income Project). In addition, the squared poverty gap is always underestimated by both parameterizations.

The biases in Gini coefficients are shown in Table 13. The underlying theoretical distributions have Gini coefficients ranging between 28.5 (Pareto) and 60.0 (Log-normal), while the surveys have inequality levels between 35.0 (Vietnam) and 45.2 (Nicaragua). We find that in all cases considered, the Gini coefficients are well estimated by POVCAL. The Beta parameterization consistently over-estimates the Gini index, but by a small margin. Both parameterizations are associated with biases of the inequality measure no larger than one percentage point.

The following conclusions emerge from this section: (a) the size of the biases does not vary monotonically with the poverty line or the number of datapoints analyzed; (b) it is difficult to find regularities in the direction of the biases; (c) neither functional form can be concluded to provide a superior fit over the other across a wide range of distributions; (d) the biases vary across the distributions considered; however, they are generally low for the country studies reported in this section; (e) in general, the Gini coefficient is well estimated.

¹⁷ We only employ four poverty lines for data corresponding to the 'hypothetical' countries, but a much wider range of poverty lines for China in order to inspect the biases associated with poverty lines situated at multiple points along the support of the income density. For Vietnam, Tanzania and Nicaragua we use the international poverty lines (\$1.08/day, \$2.15/day) and the nutritionally-anchored poverty lines proposed by Reddy, Visaria and Asali (2006).

¹⁸ For the four 'synthetic' income distributions analyzed in Table 10, we do not report biases for the poverty headcount ratio and the squared poverty gap because the conclusions are broadly similar.

| 5 | DISCUSSION AND CONCLUSIONS

In this paper we have analyzed the sign and magnitude of the biases in estimates of poverty and inequality and of the Lorenz curve that result from parametric estimation of the Lorenz curve from grouped data. In particular, we have examined the accuracy of estimates produced using two functional forms (proposed by Villasenor and Arnold, 1989 and Kakwani, 1980a) by POVCAL, a computational tool developed by the World Bank that is in widespread use by applied researchers. We have used data drawn from a large number of theoretical distributions as well as unit data from household surveys to compare POVCAL's estimates of poverty and inequality and the Lorenz curve with values from underlying distributions. We found that the two parameterizations perform relatively well in estimating poverty and inequality for distributions that are unimodal. Larger biases were identified, however, in the case of the multimodal distribution considered. The extent of misestimation of poverty does not vary predictably with , the level of poverty line, the choice of poverty indicator or even the number of datapoints. Inequality (measured by the Gini index) is well estimated.¹⁹

In our Monte Carlo study, the two parameterizations often yielded invalid Lorenz curves (e.g. negative estimated income shares). The software accurately recognized and reported these instances. An important question is whether or not the (poverty and inequality) output associated with an invalid Lorenz curve should be discarded by the researcher. We did not discover a straightforward correspondence between the validity of the estimated Lorenz curve and the accuracy of the reported estimates of poverty and inequality. In fact, despite the negative income shares often reported at the left end of the Lorenz support, poverty and inequality were still estimated with tolerable error; admittedly, the errors tend to be larger for smaller poverty lines. A similar finding was that of Kakwani (1980b) which defended the Kakwani and Podder (1976) parameterization that had been shown to give rise to theoretically invalid Lorenz curve. Kakwani (1980b) argued in favor of using invalid Lorenz curve estimates on the grounds of the parameterization's *overall* superior empirical performance in fitting a wide of observed income distributions.

Parametric estimation using POVCAL appears to provide a good fit to the Lorenz curve for a wide range of income distributions. Several non-parametric and semi-parametric density estimation techniques (e.g., nonparametric kernel density smoothing and maximum entropy density estimation) have also been recently employed on grouped income-distribution data. Minoiu and Reddy (2006) assess the accuracy of kernel density estimation in estimating poverty and inequality and compare output from that procedure with POVCAL-based estimates. They conclude that parametric estimation of Lorenz curves using POVCAL often outperforms kernel density estimation methods in the estimation of poverty and inequality. Wu and Perloff (2003) evaluate the goodness-of-fit of the maximum entropy density estimator using information on income intervals computed from underlying survey data on U.S. family income and flexible functional form assumptions. The authors find that maximum entropy density estimation performs well in estimating features of income

¹⁹ We encountered a series of technical problems with the software for input files from the multimodal and Pareto distributions (and in isolated cases, with input data from other distributions).

distributions. More research is necessary to determine whether their proposed maximum entropy method is superior to parametric Lorenz-curve fitting based on least-squares minimization (examined here).

Our results offer qualified support for the use of Lorenz curves based on parametric curve fitting, as implemented by existing software (POVCAL), when conducting applied research on poverty and income distribution.

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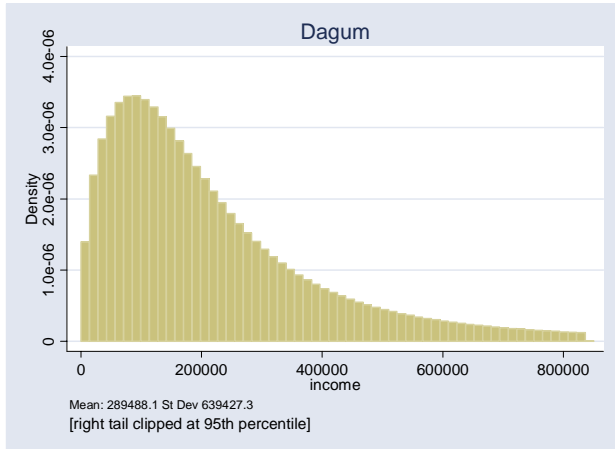
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APPENDIX

Figure 1. Distributions used in Monte Carlo analysis (Section III).

Dagum distribution



Multimodal (notional) distribution

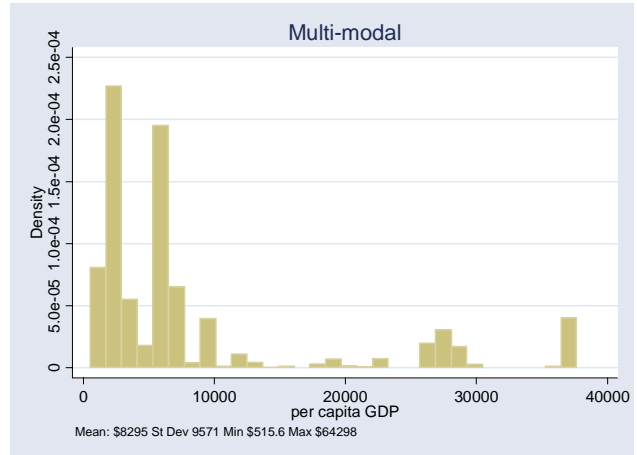
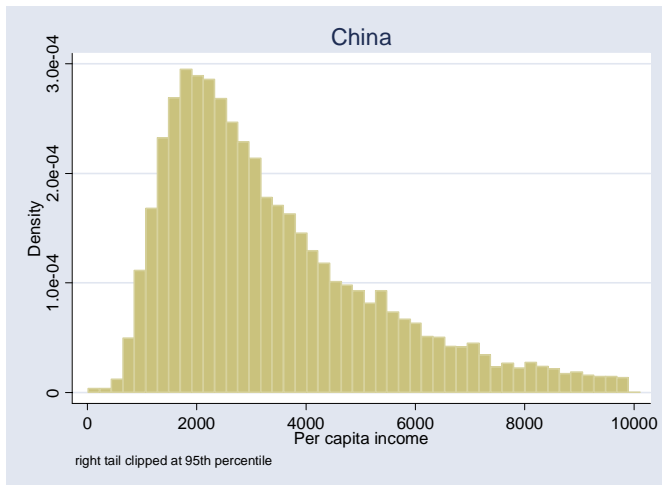
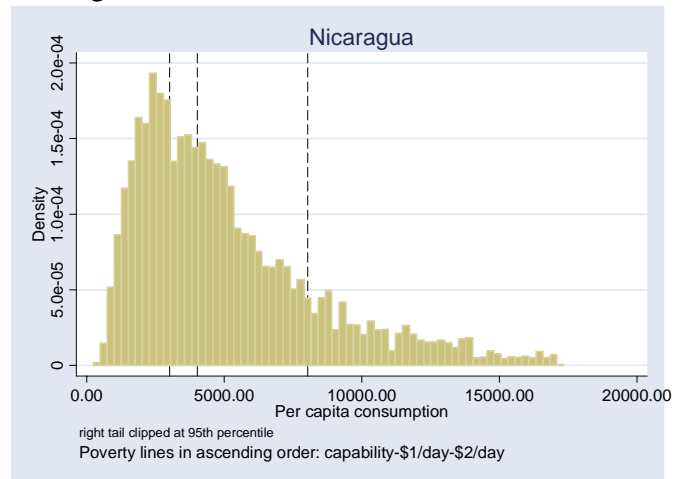


Figure 2. Distributions used for deterministic comparisons (Section IV).

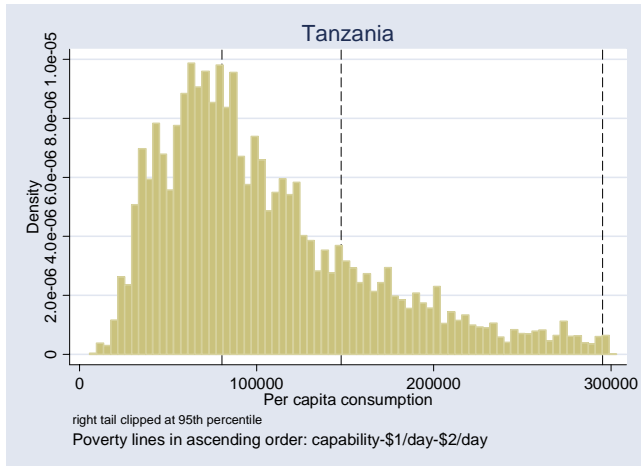
China (1995)



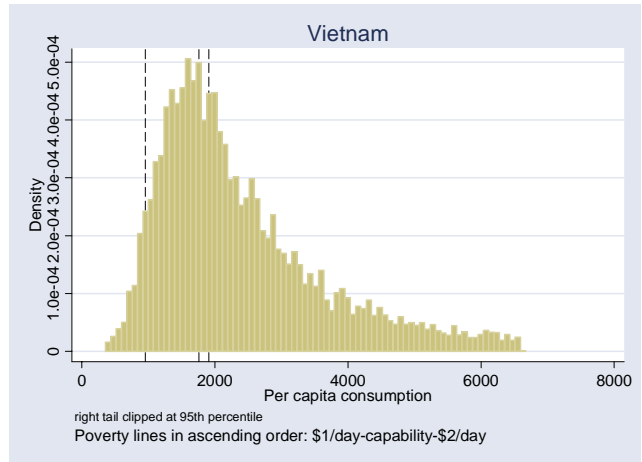
Nicaragua (1998)



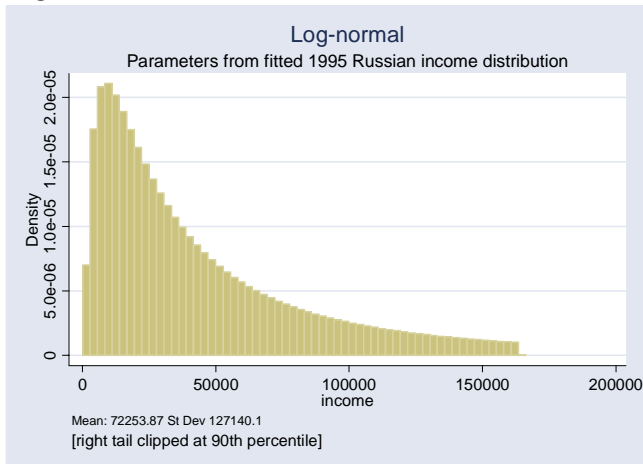
Tanzania (2001)



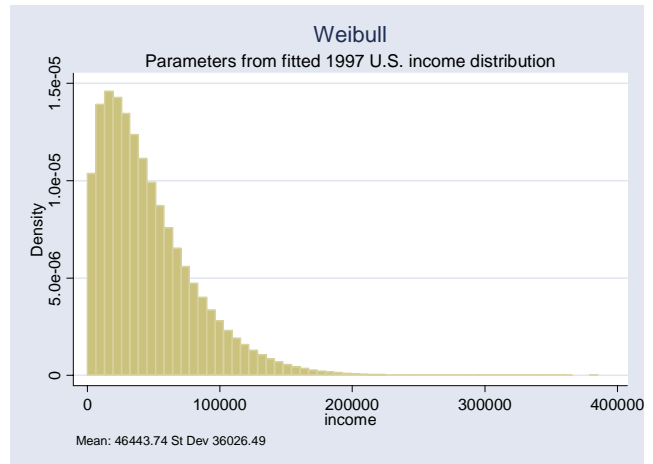
Vietnam (1998)



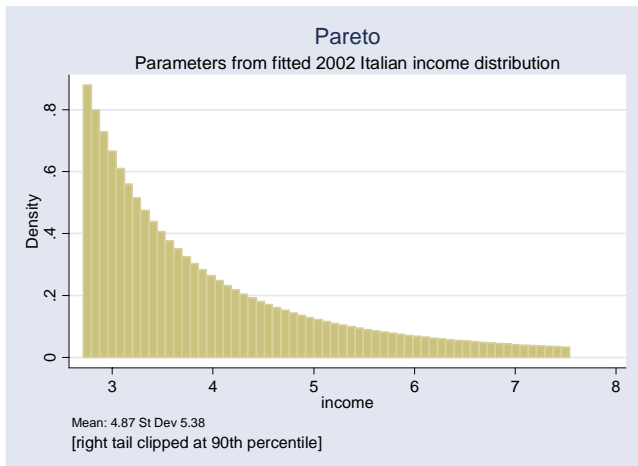
Log-normal distribution



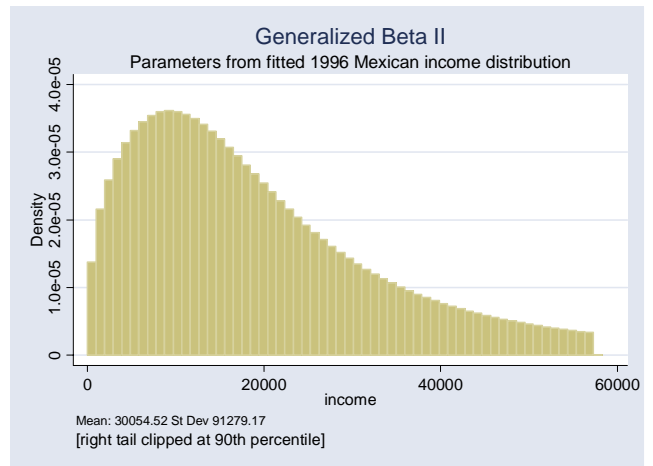
Weibull distribution



Pareto distribution



Generalized Beta II



Monte Carlo analysis. Lorenz-curve estimation (Dagum distribution)

Table 1. Sum of Squared Errors (SSE) and Sum of Absolute Errors (SAE)

	GQ			Beta		
	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
<i>Along the entire support</i>						
SSE	0.3751	0.3706	0.3689	0.3637	0.3638	0.3620
SAE	5.3502	5.3165	5.3007	5.2458	5.2697	5.2704
<i>Up to the 20th percentile of the population</i>						
SSE	0.0021	0.0020	0.0020	0.0020	0.0024	0.0027
SAE	0.1622	0.1564	0.1526	0.1537	0.1707	0.1818

Table 2. POVCAL-based Lorenz curve estimates at selected points along the support

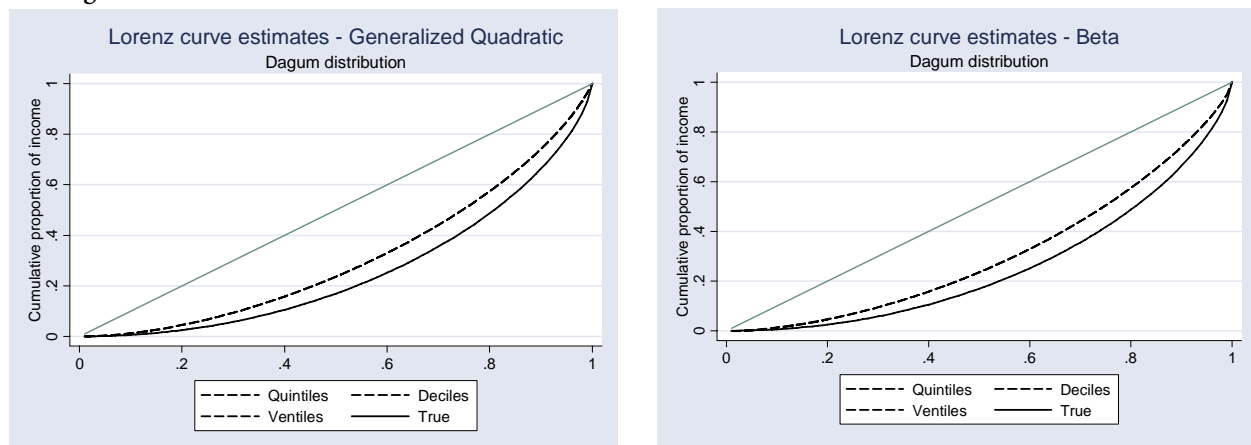
Cum. pop. prop.	True	GQ			Beta		
		Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
0.01	0.0001	0.0001	0.0000	0.0000	-0.0016	-0.0010	-0.0007
0.02	0.0002	0.0005	0.0004	0.0003	-0.0017	-0.0008	-0.0004
0.03	0.0005	0.0012	0.0010	0.0008	-0.0011	-0.0001	0.0005
0.04	0.0009	0.0021	0.0018	0.0017	-0.0002	0.0009	0.0016
0.05	0.0014	0.0032	0.0029	0.0028	0.0011	0.0023	0.0030
0.06	0.0020	0.0046	0.0043	0.0041	0.0026	0.0039	0.0047
0.07	0.0028	0.0062	0.0059	0.0056	0.0044	0.0058	0.0066
0.08	0.0037	0.0080	0.0077	0.0074	0.0064	0.0078	0.0086
0.09	0.0047	0.0101	0.0097	0.0094	0.0087	0.0101	0.0109

Table 3. Extent of underestimate or overestimate of Lorenz curve at selected points along the support

Note: positive values represent overestimate and negative values represents underestimate

Cum. pop. proportion	GQ			Beta		
	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
0.1	111%	104%	100%	90%	115%	129%
0.2	81%	80%	80%	82%	86%	89%
0.3	63%	63%	63%	63%	64%	64%
0.4	49%	50%	50%	49%	49%	49%
0.5	39%	39%	40%	39%	39%	38%
0.6	31%	31%	31%	31%	31%	30%
0.7	24%	24%	24%	24%	24%	24%
0.8	18%	18%	18%	18%	18%	18%
0.9	12%	12%	12%	11%	12%	12%

Figure 3. POVCAL-based Lorenz curve estimates



Monte Carlo analysis. Lorenz-curve estimation (Multimodal distribution)

Table 4. Sum of Squared Errors (SSE) and Sum of Absolute Errors (SAE)

	GQ			Beta		
	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
<i>Along the entire support</i>						
SSE	0.5951	0.4558	0.5048	0.2506	0.0663	0.0620
SAE	2.8596	3.4789	3.6097	1.8910	1.5521	1.7965
<i>Up to the 20th percentile of the population</i>						
SSE	0.0000	0.0149	0.0141	0.0000	0.0001	0.0002
SAE	0.0194	0.5435	0.5300	0.0157	0.0389	0.0536

Table 5. POVCAL-based Lorenz curve estimates at selected points along the support

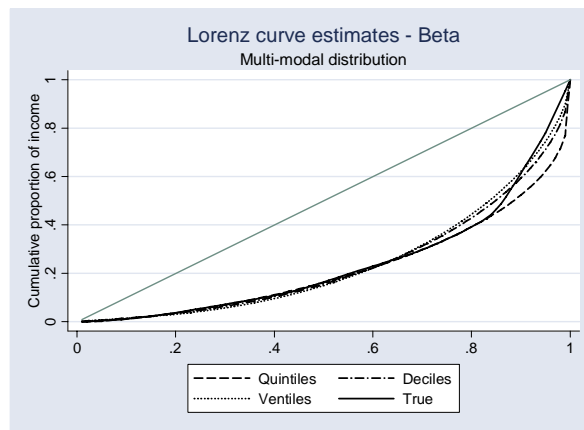
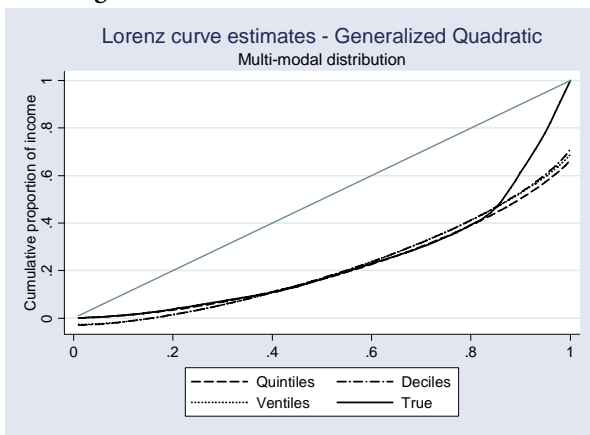
Cum. pop. prop.	True	GQ			Beta		
		Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
0.01	0.0007	0.0005	-0.0291	-0.0260	-0.0007	0.0017	0.0023
0.02	0.0015	0.0012	-0.0288	-0.0261	-0.0003	0.0031	0.0040
0.03	0.0023	0.0020	-0.0281	-0.0257	0.0005	0.0045	0.0054
0.04	0.0033	0.0029	-0.0270	-0.0250	0.0015	0.0059	0.0067
0.05	0.0044	0.0040	-0.0257	-0.0240	0.0028	0.0072	0.0080
0.06	0.0057	0.0052	-0.0241	-0.0228	0.0042	0.0086	0.0092
0.07	0.0070	0.0065	-0.0224	-0.0213	0.0058	0.0101	0.0105
0.08	0.0083	0.0080	-0.0204	-0.0196	0.0075	0.0116	0.0117
0.09	0.0099	0.0095	-0.0183	-0.0177	0.0094	0.0131	0.0130

Table 6. Extent of underestimate or overestimate of Lorenz curve at selected points along the support

Note: positive values represent overestimate and negative values represents underestimate

Cum. pop. proportion	GQ			Beta		
	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
0.1	-5%	-235%	-231%	-4%	24%	21%
0.2	-7%	-61%	-63%	-2%	-7%	-16%
0.3	-6%	-22%	-23%	-3%	-12%	-20%
0.4	2%	-1%	-1%	3%	-5%	-12%
0.5	-1%	2%	2%	-1%	-5%	-9%
0.6	-1%	3%	3%	-3%	-3%	-4%
0.7	1%	6%	7%	0%	5%	6%
0.8	0%	5%	5%	0%	9%	13%
0.9	-18%	-14%	-14%	-15%	-3%	1%

Figure 4. POVCAL-based Lorenz curve estimates



Monte Carlo analysis. Poverty and inequality biases (in percentage points)

Table 7. ALL POVERTY INDICATORS: DAGUM DISTRIBUTION

Poverty indicator	Poverty line:	Generalized Quadratic						Beta		
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles		
POVERTY	1.33 x median	66.9	0.18	0.34	0.53	-0.04	-0.21	-0.21		
HEADCOUNT	0.5 x median	21.7	-0.49	-0.67	-0.76	-0.83	-0.48	-0.21		
RATIO	0.33 x median	13.0	-0.10	-0.25	-0.27	-1.07	-1.07	-0.98		
	0.25 x median	9.1	0.01	0.03	0.05	-1.07	-1.13	-1.18		
POVERTY	1.33 x median	31.7	0.09	0.05	0.10	0.08	0.09	0.19		
GAP RATIO	0.5 x median	9.6	0.03	0.06	0.45	-0.03	-0.28	-0.30		
	0.33 x median	5.8	0.27	0.36	0.62	0.52	0.00	-0.22		
	0.25 x median	4.0	0.35	0.51	0.67	1.03	0.41	0.04		
SQUARED	1.33 x median	19.9	0.07	0.04	0.07	0.19	0.07	0.09		
POVERTY	0.5 x median	5.9	0.23	0.35	0.48	1.07	0.37	0.01		
GAP	0.33 x median	3.5	0.39	0.55	0.68	2.20	1.16	0.54		
	0.25 x median	2.4	0.47	0.68	0.84	3.36	1.80	1.02		

Table 8. ALL POVERTY INDICATORS: MULTIMODAL DISTRIBUTION.²⁰

Poverty indicator	Poverty line:	Generalized Quadratic						Beta		
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles		
POVERTY	1.33 x median	71.3	1.95	-1.72	-1.79	0.38	-7.04	-9.74		
HEADCOUN	0.75 x median	43.5	-2.55	-6.90	-7.83	-0.43	-1.05	-1.38		
T RATIO	\$2.15/day	4.2	0.26	-	-	-0.60	-	-		
	\$1.08/day	0.0	-	-	-	-	-	-		
POVERTY	1.33 x median	34.90	0.34	-1.20	-1.40	0.65	-0.51	-0.44		
GAP RATIO	0.75 x median	18.17	-0.92	0.26	0.32	-1.00	0.81	2.30		
	\$2.15/day	0.97	0.38	-	-	1.65	-	-		
	\$1.08/day	0.0	-	-	-	-	-	-		
SQUARED	1.33 x median	21.33	0.41	1.47	1.15	0.61	1.00	1.97		
POVERTY	0.75 x median	9.80	0.16	4.78	4.07	0.00	0.85	2.33		
GAP	\$2.15/day	0.25	0.35	-	-	3.78	-	-		
	\$1.08/day	0.0	-	-	-	-	-	-		

Table 9. GINI COEFFICIENT: DAGUM AND MULTIMODAL DISTRIBUTIONS.

Inequality indicator:	Distribution:	Generalized Quadratic						Beta		
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles		
GINI	Dagum	38.17	-0.22	-0.15	-0.12	0.03	-0.04	-0.04		
COEFFICIENT	Multimodal	52.43	5.10	3.59	4.53	3.73	0.64	-0.12		

²⁰ Interestingly, the international \$1.08/day poverty line (at 1993 international US\$) produces zero poverty estimates since the lowest per capita GDP in 2004 was \$515 (Sierra Leone) while the yearly equivalent of the \$1.08/day poverty line is \$448. This latter finding suggests that, if we take the estimates of per-capita real incomes and the lower money-metric international poverty line as given, the vast majority of world poverty must be inferred to arise from uneven intra-national income distributions.

Box 1. Technical problems with input data from the multimodal distribution

Examples of technical problems encountered when using POVCAL on input files representing income profiles computed with data drawn from the multimodal distribution.

Input data: Ventile means

Number of input files (draws): 100

- In one case, the Gini coefficient was reported to be 114.9275, the headcount ratio was almost 86 percent (as compared to a true value of 4 percent), the poverty gap ratio was reported to be negative and the squared poverty gap was higher than 900 (as compared to a true value of 0.25). We did not include this assessment
- In two cases, the program reported output only for the BETA parameterization
- In four cases, the program did not report output for the GQ parameterization and the lowest poverty line, and only reported output for the BETA parameterization for the higher poverty lines.
- In 91/100 cases, the BETA output was not reported for at least one poverty line because that poverty line was deemed outside the admissible bounds (i.e., too low).
- In eight cases, the GQ-based squared poverty gap was estimated to be higher than 100 (as compared to the true counterpart of 0.25). In three cases, it was reported to be negative (these three last cases were not included in the assessment).

Country studies. Poverty and inequality biases (in percentage points)

Table 10. POVERTY HEADCOUNT RATIO: VIETNAM, TANZANIA AND NICARAGUA

Distribution:	Poverty line:	GQ				Beta		
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
Vietnam 1998	\$1/day	5.2	-1.00	-1.10	-0.19	-0.77	-0.51	-
	Capability	35.7	0.17	0.30	1.71	0.11	0.04	-
	\$2/day	41.9	-0.40	-0.35	1.52	-0.35	-0.64	-
Tanzania 2001	Capability	40.4	-0.30	-0.15	-0.13	-0.25	-0.23	-0.20
	\$1/day	75.4	1.00	0.64	0.57	1.04	0.33	-0.23
	\$2/day	97.8	0.34	0.19	0.16	-	0.96	0.94
Nicaragua 1998	Capability	30.6	-0.45	-0.30	-0.24	-0.62	-0.42	-0.27
	\$1/day	44.6	0.09	0.14	0.18	0.35	0.31	0.29
	\$2/day	79.0	0.58	0.26	0.17	0.40	0.10	-0.12

Table 11. POVERTY HEADCOUNT RATIO: WEIBULL, GENERALIZED BETA II, LOG-NORMAL AND PARETO

Distribution:	Poverty line:	GQ				Beta		
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
United States 1997 / Weibull	0.33 x median	15.1	0.18	0.13	0.11	0.33	0.60	0.86
	0.66 x median	33.2	-0.29	-0.26	-0.34	0.10	0.13	0.17
	1.33 x median	63.4	0.13	0.28	0.34	-0.20	-0.57	-0.86
	1.66 x median	73.8	-0.05	0.18	0.27	0.24	-0.12	-0.43
Mexico 1996 / Generalized Beta II	0.33 x median	13.7	0.57	0.62	0.62	-0.66	-0.49	-0.30
	0.66 x median	32.5	0.25	0.50	0.64	0.08	0.36	0.59
	1.33 x median	62.9	-0.30	-0.49	-0.53	-0.10	-0.25	-0.38
	1.66 x median	72.0	0.09	-0.30	-0.43	-0.04	-0.27	-0.47
Russia 1995 / Log-normal	0.33 x median	17.6	0.61	0.64	0.65	2.02	2.58	3.07
	0.66 x median	36.3	0.05	0.12	0.12	-0.04	-0.28	-0.41
	1.33 x median	59.5	-0.17	-0.20	-0.20	-0.78	-1.61	-2.24
	1.66 x median	66.5	-0.06	-0.12	-0.12	-0.28	-1.15	-1.84
Italy 2002 / Pareto	1.33 x median	73.7	-0.09	-0.03	0.00	0.29	-0.30	-0.76
	1.50 x median	79.9	-0.08	0.00	-1.51	0.89	0.41	-1.71
	1.66 x median	84.0	-0.24	-0.15	-0.11	-	-	-
	2.00 x median	89.5	-0.20	-0.09	-0.05	-	-	-

Table 12. ALL POVERTY INDICATORS: CHINA.

POVERTY HEADCOUNT RATIO						
Poverty line: Median x	Quintiles		Deciles		Ventiles	
	GQ	Beta	GQ	Beta	GQ	Beta
2.00	-0.13	-	0.05	-	0.10	-
1.75	0.43	0.81	0.59	0.66	0.64	0.44
1.66	0.35	0.63	0.51	0.45	0.55	0.22
1.50	0.17	0.22	0.30	0.00	0.33	-0.27
1.33	-0.11	-0.24	-0.05	-0.51	-0.03	-0.79
1.25	-0.18	-0.36	-0.15	-0.64	-0.15	-0.92
1.00	-0.55	-0.67	-0.64	-0.96	-0.67	-1.18
0.75	0.29	0.26	0.14	0.06	0.10	0.02
0.50	0.94	0.80	0.83	0.70	0.79	0.75
0.33	1.36	0.88	1.42	1.05	1.43	1.26
0.25	-2.43	-0.95	-2.04	-0.56	-1.94	-0.41
0.20	-6.30	-0.58	-5.71	-0.44	-5.56	-0.41

POVERTY GAP RATIO						
Poverty line: Median x	Quintiles		Deciles		Ventiles	
	GQ	Beta	GQ	Beta	GQ	Beta
2.00	0.00	-	0.04	-	0.05	-
1.75	-0.02	-6.02	0.01	-0.12	0.01	-0.22
1.66	-0.04	-0.06	-0.02	-0.16	-0.02	-0.24
1.50	-0.08	-0.13	-0.08	-0.22	-0.09	-0.28
1.33	-0.11	-0.15	-0.12	-0.22	-0.12	-0.26
1.25	-0.10	-0.14	-0.12	-0.19	-0.12	-0.22
1.00	-0.02	-0.02	-0.03	-0.02	-0.04	0.02
0.75	0.07	0.08	0.10	0.18	0.10	0.27
0.50	-0.02	0.01	0.03	0.14	0.04	0.24
0.33	-0.42	-0.29	-0.35	-0.13	-0.33	-0.03
0.25	-0.63	-0.29	-0.62	-0.33	-0.62	-0.31
0.20	0.52	-0.30	0.37	-0.28	0.33	-0.27

SQUARED POVERTY GAP						
Poverty line: Median x	Quintiles		Deciles		Ventiles	
	GQ	Beta	GQ	Beta	GQ	Beta
2.00	-0.09	-	-0.08	-	-0.08	-
1.75	-0.12	-0.12	-0.11	-0.14	-0.11	-0.15
1.66	-0.12	-0.13	-0.12	-0.14	-0.12	-0.14
1.50	-0.14	-0.14	-0.13	-0.13	-0.14	-0.11
1.33	-0.15	-0.13	-0.14	-0.10	-0.14	-0.06
1.25	-0.16	-0.13	-0.15	-0.09	-0.15	-0.04
1.00	-0.20	-0.15	-0.18	-0.07	-0.17	0.00
0.75	-0.39	-0.30	-0.35	-0.19	-0.33	-0.11
0.50	-0.52	-0.41	-0.47	-0.29	-0.46	-0.22
0.33	-0.76	-0.62	-0.73	-0.53	-0.72	-0.49
0.25	-0.94	-0.62	-0.94	-0.86	-0.94	-0.86
0.20	-1.47	-1.29	-1.43	-1.28	-1.42	-1.28

Table 13. GINI COEFFICIENT: ALL DISTRIBUTIONS.

Inequality indicator:	Distribution:	GQ			Beta			
		<i>True</i>	Quintiles	Deciles	Ventiles	Quintiles	Deciles	Ventiles
GINI COEFFICIENT	China 1995	38.6	-0.18	-0.11	-0.10	0.07	0.02	-0.04
	Tanzania 2001	37.2	0.58	0.56	-0.26	0.83	0.69	-
	Vietnam 1998	35.0	0.24	0.07	0.04	0.36	0.14	0.03
	Nicaragua 1998	45.2	0.22	0.08	0.09	0.19	0.09	0.08
	Weibull	41.3	-0.14	-0.07	-0.04	0.15	0.06	0.01
	Generalized Beta II	54.7	0.49	0.25	0.16	0.19	0.10	0.05
	Log-normal	60.0	0.04	-0.03	-0.02	0.68	0.31	0.07
	Pareto	28.5	-0.08	-0.04	-0.01	-	-	-

Note: In Tables 10-13, the cells with missing values correspond to instances in which POVCAL shut down due to apparent software error before reporting the results for the Beta parameterization.

About the Authors

Camelia Minoiu is a Ph.D. candidate in the Department of Economics at Columbia University. Her current research interests are in the area of nonparametric density estimation methods used in assessing income poverty and inequality. Previous work includes a sensitivity analysis of the extent and trend of Chinese poverty to underlying assumptions, an analysis of the vulnerability of rural households in transition economies to negative income shocks (with an application to Romania), as well as an identification and explanation of real income growth patterns in a cross section of countries over the past four decades.

Sanjay G. Reddy is an Assistant Professor of Economics at Barnard College at Columbia University. He also instructs courses on world poverty and development economics at Columbia University's School of International and Public Affairs. His areas of work include development economics, international economics, and economics and philosophy. He possesses a Ph.D. in Economics from Harvard University, an M.Phil. in Social Anthropology from the University of Cambridge, and an A.B. in Applied Mathematics with Physics from Harvard University. He has held fellowships from the Center for Ethics and the Professions and the Center for Population and Development Studies at Harvard University and the Center for Human Values at Princeton University. Reddy is presently working extensively on global poverty and inequality estimates, capability-based inter-country poverty comparisons, and the theory of economic and social measurement generally (including index number analysis).

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420 West 118th Street
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