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Global Inequality

Recent Evidence and Trends

Duangkamon Chotikapanich,[1]
D.S. Prasada Rao,[2]
William E. Griffiths,[3]
and Vicar Valencia[3]

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Abstract

This paper examines the nature and extent of global and regional income distribution and inequality using the most recent country level data on income distribution drawn from World Bank and UNU-WIDER studies for the period 1993–2000. The methodology used is a recently developed technique to fit flexible income distributions to limited aggregated data. Empirical results show a very high degree of global inequality, but with some evidence of inequality decreasing between the two years.

Keywords: Gini coefficient, beta-2 distribution

JEL classification: C13, C16, D31

[1]Corresponding author: Monash University, Department of Econometrics and Business Statistics, Melbourne, Australia, email: Duangkamon.Chotikapanich@BusEco.monash.edu.au
[2]University of Queensland, Department of Economics, Australia
[3]University of Melbourne, Department of Economics, Australia

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The tables and figures are at the end of the paper.

UNU World Institute for Development Economics Research (UNU-WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1 Introduction

In the current climate of increasing globalization and a push for free trade among nations through the World Trade Organization, there is considerable interest among economists, international development organizations and the general public concerning the overall effects of globalization on the welfare of the global society. There is a concern that increasing globalization may lead to increasing inequality, and that increasing global inequality may mean the unsustainability of the current international order. A major difficulty with the ongoing debate about globalization is the problem of measuring the extent of inequality, and being able to meaningfully compare inequality across countries, regions or time periods. Unless global and regional inequality are accurately measured, it is difficult to evaluate whether various policy initiatives such as moves towards greater globalization are increasing or reducing inequality.

The process of globalization is perceived to create winners and losers, thus leading to greater inequality. At the country level, it is possible that in the short-run only certain sections and population sub-groups benefit from increased trade and deregulation. Also, in the process of achieving increased levels of efficiency and productivity it is conceivable that capital-augmenting and labour-shedding technologies may be preferred, leading to increases in unemployment levels. This outcome is a scenario that points towards increasing inequality within the countries that are active pursuants of globalization. Moving from the country level to the regional level, globalization is likely to result in varying levels of growth in real per capita income achieved in different countries and regions. It is now well documented that countries in East and South East Asia have experienced strong growth in income and living standards. However, performance even within this region is not uniform. Chotikapanich and Rao (1998) have documented this uneven growth performance and its effects on inequality within this region. The African and Latin American regions have lagged behind the Asian region in terms of growth performance. Evidence to date (Chotikapanich et al., 1997; Chotikapanich and Rao, 1998; Melchior, Telle and Wiig, 2000; Milanovic and Yitzhaki, 2001; and Milanovic, 2002) indicates a steady reduction in inequality *between* countries during the period 1960s to 1998, but, at the same time, there has been an increase in global inequality. This finding can largely be attributed to increases in income inequality within countries. Studies which ignore within country inequality have shown a reduction in global inequality. Schulz (1998), Firebaugh (1999) and Melchior, Telle and Wiig (2000) report a decline in global inequality measured using inter-country differences in income.

Within the context of assessing the implications of increased globalization on total welfare, it is necessary to accurately measure inequality at the global, regional and country levels. Despite the increasing recognition of the need to measure inequality on a regular basis at regional and global levels, availability of detailed data from countries is quite limited. Most of the data for the purpose of measuring inequality are drawn from household expenditure and income surveys that are conducted once in five years in most countries. Some countries conduct these surveys more regularly. Compilation of data from these surveys and data dissemination is resource intensive and, consequently, much of these data are not readily available for researchers. More regularly disseminated data take the form of summary statistics that include measures of inequality like the Gini Coefficient and incomes shares of quintile or decile groups.

A significant research problem arises from the need to study regional and global distributions of income based on income distribution data available in a summary form. There have been several attempts in the past addressing these issues. Starting from some earlier work by Theil (1979, 1989 and 1996) where regional and global inequality were estimated ignoring within-country inequality, Chotikapanich et al. (1997 and 1998) estimated global inequality using a restrictive lognormal distribution as a model of income distribution within each country. More recently, Milanovic (2002) uses data from World Bank sources to generalize the work of Chotikapanich et al. and to study global inequality and its decomposition into regional inequality. Although the most recent study by Milanovic (2002) makes use of extensive income distribution data available from various sources, principally from the World Bank, the approach makes use of only the income shares of quintile and decile population groups. An assumption implicit in the study is that all people in a given group, bottom 10 per cent say, receive the same income which is equal to the average income for that group. Sala-i-Martin (2002a, 2002b) reports a similar study with a slightly different approach where country-specific kernel density functions are estimated for each country separately for each year in the study. His study also starts with the assumption that all individuals in a quintile or decile group have the same income. Thus, Milanovic (2002) and Sala-i-Martin (2002a, 2002b) both ignore distributional characteristics within each population sub-group in each of the countries included. In addition to the general limitations of the studies listed above, work on the global income distribution does not always make use of the latest econometric techniques available for the purpose of studying this important problem.

The aim of the paper is to estimate global and regional income distributions using less restrictive assumptions than those employed in earlier studies for the income distributions of individual countries. In particular, the lognormal assumption made by Chotikapanich et al. (1997) and the constant-income-within-subgroups assumption made by Milanovic (2002) and Sala-i-Martin (2002a, 2002b) are relaxed. Once global and regional income distributions are estimated we can analyze global and regional inequality levels and trends using inequality measures. Income distributions will be compared using stochastic dominance criteria and a decomposition analysis will be performed.

2 Modelling income distributions using limited data

A number of past studies have tried to estimate global income distributions. Examples of those that use some method for taking into account the inequality within countries are Chotikapanich, Valenzuela and Rao (1997), Milanovic (2002) and Sala-i-Martin (2002a, 2002b). Milanovic (2002) used country grouped data on income classes to obtain the population in each income class and the class mean incomes. He then combined this information across countries to obtain regional and global income distributions. Sala-i-Martin (2002a, 2002b) estimates country income distributions by performing kernel density estimation on country data grouped into income classes. A previous study that is similar to our current paper is that by Chotikapanich, Valenzuela and Rao (1997) who used a lognormal distribution to model income distributions for each country. While the lognormal distribution is relatively easy to estimate from information on the Gini coefficients and mean income for each country, it is known to be restrictive in that it implies symmetric and non-intersecting Lorenz curves.

Given the aggregated nature of income distribution data available for each country, in the form of population shares and mean incomes or income shares for different income classes, in this paper we make use of a recently developed technique to fit flexible income distributions to limited aggregated data. In this section we briefly outline the methodology, which involves three stages. At the first stage, we fit a statistical distribution to the income distribution of each country. We consider a special case of the generalized beta distribution, viz., the beta-2 distribution. We utilize recently developed econometric methodology based on the generalized method of moments (GMM) to estimate the parameters of the beta-2 distribution. In the second stage we derive regional and global income distributions by combining distributions for each country. This approach is based on the notion that the overall distribution is a population-share weighted mixture of income distributions for different countries. Finally, income distributions derived at the regional or global level are used in studying the levels and trends in inequality using Lorenz curves and the estimated Gini and Theil coefficients.

Section 2.1 summarizes a method for estimating the beta-2 parameters, and the class limits of the grouped data. Methods for combining the country-specific income distributions and exploring the characteristics of the resulting regional income distributions are given in Section 2.2. Section 2.3 provides a method for decomposition of income inequality using the Gini and Theil indices. Properties of Lorenz dominance and stochastic dominance are discussed in Section 2.4.

2.1 Modelling country income distributions

Because the available data are aggregated, in the form of population shares and mean incomes for different income classes, using the aggregated form directly underestimates the income inequality. If we can fit a suitable statistical distribution to the aggregated income distribution of each country it may improve estimation of inequality. A large number of probability density functions have been suggested in the literature for modelling income distributions. See, for example, McDonald and Ransom (1979), McDonald (1984), McDonald and Xu (1995), Creedy and Martin (1997), Bandourian, McDonald and Turley (2002) and Kleiber and Kotz (2003). The one we have chosen for our analysis is a member of the generalized beta distribution (see McDonald and Xu 1995) known as the beta-2 distribution. The beta-2 distribution has been extensively used in modelling income distribution data; it has a number of convenient analytical properties, and, as we will see, it provides a very good fit to the observed data. In addition, the beta-2 distribution has the desirable property that the marginal distributions of the total income and expenditure aggregates follow beta-2 distributions. As a corollary, the Gini coefficients for the aggregate and their components have the same functional forms but with different parameter values. The beta-2 distribution is also a flexible distribution that has been shown to provide a good fit to a variety of empirical income distributions. See for example McDonald (1984) and McDonald and Ransom (1979).

In this paper we will assume that country income distributions can be modelled using a beta-2 distribution with three parameters. The probability density function (pdf) is defined as:

$$f(y) = \frac{y^{p-1}}{b^p B(p,q)\left(1+\frac{y}{b}\right)^{p+q}} \qquad y > 0 \tag{1}$$

where $b > 0, p > 0$ and $q > 0$ are parameters and

$$B(p,q) \;=\; \frac{\Gamma(p)\,\Gamma(q)}{\Gamma(p+q)} \;=\; \int_0^1 t^{p-1}(1-t)^{q-1}\,dt$$

For the mode of $f(y)$ to be non-zero $p > 1$ is required; for the mean to exist $q > 1$ is required.

Its corresponding cumulative distribution function (cdf) is given by

$$F(y) \;=\; \frac{1}{B(p,q)} \int_0^{[y/(b+y)]} t^{p-1}(1-t)^{q-1}\,dt \;=\; B_{y/(b+y)}\left(p,\ q\right) \tag{2}$$

The function $B_t(p,q)$ is the cdf for the normalized beta distribution defined on the (0, 1) interval. It is a convenient representation because it is commonly included as a readily-computed function in statistical software. If T is a standard beta random variable defined on the interval (0, 1), then the relationship between T and Y is

$$T = \frac{Y}{b+Y} \qquad Y = \frac{bT}{1-T}$$

The mean, mode and variance of Y are given by

$$\mu = \frac{bp}{q-1} \qquad m = \frac{(p-1)b}{q+1}$$

$$\sigma^2 \;=\; \mu\left[\frac{b(p+1)}{q-2} - \mu\right] \;=\; \frac{b^2 p(p+q-1)}{(q-1)^2(q-2)} \tag{3}$$

The estimation procedure requires starting values for b, p and q. It is often easier to suggest reasonable starting values for μ, m and σ^2. In this case corresponding values for b, p and q can be found from the relationship between parameters of the distribution and the standard measures like the mean, mode and the variance:

$$b = \frac{\mu^2(\mu - m) - (3m - \mu)\sigma^2}{\sigma^2 - \mu^2 + \mu m}$$

$$p = \frac{\mu}{b}\left(\frac{2m+b}{\mu - m}\right) \qquad q = \frac{\mu + m + b}{\mu - m} \tag{4}$$

For future reference we note that the Gini coefficient is given by

$$G = \frac{2B(2p, 2q-1)}{pB^2(p,q)} \tag{5}$$

If the parameters *b*, *p* and *q* are known, then the distribution is completely known and the Gini coefficient can be computed. To estimate these three parameters we use the method proposed by Chotikapanich, Griffiths and Rao (2007) who developed econometric methodology based on the generalized method of moments (GMM) to estimate the parameters of the beta-2 distribution. The procedure can be summarized as follows:

Suppose we have *N* income classes $(a_0, a_1), (a_1, a_2), \ldots, (a_{N-1}, a_N)$, with $a_0 = 0$ and $a_N = \infty$. Let the mean class incomes for each of the *N* classes be given by $\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_N$; and let the population proportions for each class be given by $c_1, c_2, \ldots, c_N$. Given available data on $\bar{y}_i$ and c_i, but not on a_i, our problem is to estimate the parameters of a beta-2 distribution, along with the unknown class limits $a_1, a_2, \ldots, a_{N-1}$. The approach we use is to fit a beta distribution to the data such that the sample moments $\bar{y}_i$ and c_i are 'close' to their population counterparts. This approach is equivalent to fitting a distribution such that $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{2N}$ are 'close to zero' where

$$c_i = \int_{a_{i-1}}^{a_i} f(y)dy + \varepsilon_i \qquad i = 1, 2, \ldots, N \tag{6}$$

and

$$\bar{y}_i = \frac{\int_{a_{i-1}}^{a_i} yf(y)dy}{\int_{a_{i-1}}^{a_i} f(y)dy} + \varepsilon_{N+i} \qquad i = 1, 2, \ldots, N \tag{7}$$

Chotikapanich, Griffiths and Rao (2007) show how to find estimates of the parameters, *b, p, q* and the class limits $a_1, a_2, \ldots, a_{N-1}$ that minimize the weighted sum of squares function

$$\sum_{i=1}^{N}\left[\left(\frac{\varepsilon_i}{c_i}\right)^2 + \left(\frac{\varepsilon_{N+i}}{\bar{y}_i}\right)^2\right] \tag{8}$$

This can be achieved by recognizing that equations (6) and (7) can be rewritten in terms of the beta distribution function as follows:

$$c_i \;=\; B_{a_i/(b+a_i)}\left(p,q\right)-B_{a_{i-1}/(b+a_{i-1})}\left(p,q\right) \;+\; \varepsilon_i \tag{9}$$

and

$$\bar{y}_i \;=\; \frac{bp}{q-1}\left(\frac{B_{a_i/(b+a_i)}\left(p+1,q-1\right)-B_{a_{i-1}/(b+a_{i-1})}\left(p+1,q-1\right)}{B_{a_i/(b+a_i)}\left(p,q\right)-B_{a_{i-1}/(b+a_{i-1})}\left(p,q\right)}\right) \;+\; \varepsilon_{N+i} \tag{10}$$

where $B_{a_0/(b+a_0)}\left(p,q\right)=0$ and $B_{a_N/(b+a_N)}\left(p,q\right)=1$.

The estimation can be done using the non-linear least squares options available in a standard econometric package like EViews.[1] Starting values for the non-linear optimization problem are derived using descriptive statistics from the sample relating to the population moments described in equation (3).

2.2 Method for combining income distributions for different countries

Suppose we have K countries. After estimating the income distributions we are in a position to combine them to form a regional or global income distribution. Given K countries each with a beta income pdf, $f_k(y),\ k=1,2,\ldots,K$, and population proportions $\lambda_1,\lambda_2,\ldots\lambda_K$, the pdf for the income distribution for the region is given by the mixture

$$f(y) \;=\; \sum_{k=1}^{K}\lambda_k f_k(y) \tag{11}$$

The regional/global cumulative distribution function is given by the same weighted average of the country cdfs

$$F(y) \;=\; \sum_{k=1}^{K}\lambda_k F_k(y) \;=\; \sum_{k=1}^{K}\lambda_j B_{y/(y+b_k)}\left(p_k,q_k\right) \tag{12}$$

Regional/global mean income is given by

$$\mu \;=\; \sum_{k=1}^{K}\lambda_k\mu_k \;=\; \sum_{k=1}^{K}\frac{\lambda_k b_k p_k}{q_k-1} \tag{13}$$

1 The code used in estimating parameters of the beta-2 distribution using EViews is available with the authors if some readers are interested in using this approach.

The regional/global cumulative income shares are given by

$$\begin{aligned}\eta(y) &= \frac{1}{\mu}\int_0^y z\, f(z)\,dz \\ &= \frac{1}{\mu}\sum_{k=1}^{K}\lambda_k \int_0^y z\, f_k(z)\,dz \qquad (14) \\ &= \frac{1}{\mu}\sum_{k=1}^{K}\lambda_k\,\mu_k\, B_{y/(y+b_k)}\left(p_k+1, q_k-1\right)\end{aligned}$$

where $\mu_k = b_k p_k/(q_k-1)$.

A regional/global cumulative distribution function can be graphed by using equation (12) to compute $F(y)$ for a grid of values of y. A regional Lorenz curve, relating income shares to population shares, can be graphed by using equations (12) and (14) to compute $F(y)$ and $\eta(y)$ for a grid of values of y.

The regional Gini coefficient is calculated using η_i and F_i that are obtained from $\eta(y)$ and $F(y)$ for a grid of values of y. The expression is:

$$Gini = \sum_{i=1}^{N}\eta_{i+1}F_i - \sum_{i=1}^{N}\eta_i F_{i+1} \qquad (15)$$

Let $q_i = \eta_i - \eta_{i-1}$ be the income shares for income class i, and $p_i = F_i - F_{i-1}$ be the corresponding population share. The regional Theil L index is calculated as:

$$Theil = \sum_{i=1}^{N} p_i \ln\left(\frac{p_i}{q_i}\right) \qquad (16)$$

In fact, once the distributions at the country level are derived, these income distributions offer the possibility of undertaking in depth analysis of regional or global income inequality.

2.3 Decomposition of income inequality

When considering regional or global income inequality it is also informative to decompose total inequality into the contributions from different population subgroups. Once way to decompose a Gini coefficient is

$$Gini = G_W + G_B + I$$

where G_W is the component of total inequality which is the contribution from within country inequality. It is defined as $G_W = \sum_{k=1}^{K}\frac{N_k}{N}\frac{Y_k}{Y}Gini_k$, where N_k and Y_k are the total population and total income, respectively for country k, and N and Y are the total regional or global population and income, respectively.

G_B is the component of total inequality due to the inequality between countries. It is the total inequality calculated when every person in a given country is given the mean income of that country.

I is the component of the total inequality which is the residual. It is also known as the interaction effect or overlapping component. It takes into account the degrees of overlapping of the income distributions between countries.

Decomposition of the Theil inequality index is more straightforward because it is additively decomposable. It can be decomposed as

$$Theil = T_W + T_B$$

where T_W measures inequality within countries; it is defined as $\sum_{k=1}^{K}(N_k/N)Theil_k$.

T_B is the inequality between countries; it is defined as $\sum_{k=1}^{K}\frac{N_k}{N}\ln\left(\frac{N_k/N}{Y_k/Y}\right)$.

2.4 Lorenz and stochastic dominance

Another interesting aspect when comparing two income distributions is the issue of Lorenz or stochastic dominance. Comparisons of Lorenz curves or income distributions can be done, for example, between two countries, between two regions or between two different time periods. At the country level after country income distributions are estimated, Lorenz dominance that compares Lorenz curves between countries or between two periods of time can easily be examined using properties of the beta-2 distribution. However, at the regional/global level, after we combine country income distributions, the examination of dominance conditions is not as straight forward.

Consider first the country level. Using properties of the beta-2 distribution, Lorenz dominance between countries and over time can be examined by comparing the parameters of the distributions using a sufficient condition described in Wilfing (1996). A distribution function $F(y)$ is said to exhibit less inequality in the Lorenz sense than a distribution $H(y)$, $F \leq_L H$, if the Lorenz curve of F is greater than (lies above) or equal to the Lorenz curve of H. Given that the income distributions of country i and j follow a beta distribution, then a sufficient condition for the income distribution of country i to Lorenz dominate (have less inequality) than that for country j is (Wilfling 1996)

$$p_j \leq p_i \quad \text{and} \quad q_j \leq q_i$$

For stochastic dominance (first or second order) there is no easy way to observe the property by comparing parameters as for the case of Lorenz dominance. However, the dominance property may be investigated by comparing the distributions at a large number of income points. If one distribution is greater than (to the right) or equal to the other distribution we can then conclude that dominance exists.

For the case of regional/global comparisons, the Lorenz curves or income distributions are defined in terms of mixtures of beta-2 distributions. Dominance can only be examined by comparing the Lorenz curves or distributions at a large numbers of income points.

3 Description of data and sources

3.1 Data sources

This paper estimates global income distributions for the years 1993 and 2000. The data on country income distributions used to estimate global income distributions are from two main sources: the World Bank and the World Institute for Development Economics Research (UNU-WIDER). The World Bank has long been a major provider of income-distribution data for the purpose of cross-country research. Recent work by Milanovic (2002) who examined global income distributions for the years 1988 and 1993 is based on a set of cross-country data that he compiled for the World Bank, data are available for more than 100 countries. They are in the form of mean incomes for a number of income classes. The UNU-WIDER database version used in this paper is known as 'UNU-WIDER World Income Inequality Database Version 2.0a, June 2005' or WIID2a. It is an update of the Deininger and Squire database from the World Bank, with new estimates from the Luxembourg Income Study and Transmonee, and other new sources as they have become available. The URL for WIID2a is http://www.wider.unu.edu/wiid/wiid.htm. Data from WIID2a are available for more than 150 countries or areas with a time span from before 1960 to 2003. However, the data available for the majority of countries are between 1985 and 2000. The data are in the form of income (expenditure) and population shares for a number of income classes. In the current paper, to facilitate comparison of our results with those of Milanovic, the data we use for 1993 are from the World Bank and we extend the results to examine the global income distribution for 2000 using the data from WIID2a.

Both sources of data provide information for each country on class mean incomes (or expenditures) in local currency or income shares for a number of income classes, ranging from as low as 5 to 20. For each income class the population share is known. In terms of analysis, we start with as many countries as possible. We found that for some countries with only 5 income classes the estimations were unstable producing the results for estimated means and Gini coefficients which are not consistent with the means reported by PWT6.1 and the Gini coefficients reported by WIID2a. For those cases we dropped them from the analysis.

Ideally distribution data should refer either to income or expenditure of persons or households. In the World Bank data set for 1993, there is a mix of per capita income and per capita expenditure. The WIID2a data set provides data from a variety of sources/surveys for some countries and for some years. There is a mix of per capita income and per capita expenditure for individual, family or household units. Our preference is to use per capita household income. If this is not available our next preference is per capita household expenditure. These differences could influence the estimates of the parameters of the respective 'income' distributions.

To derive a regional or global income distribution, nominal per capita income for each country needs to be adjusted for differences in prices across countries, and for purposes of temporal welfare comparisons further adjustments are necessary for movements in prices over time. To describe how such adjustments are made, consider first the original data from each country in one particular year. Let $\overline{x}_i$ = class mean income (or expenditure) in local currency, and c_i = population share for the i-th income class. Based on these data we calculate the income share for each income class as $g_i = \overline{x}_i c_i \big/ \sum \overline{x}_j c_j$. To adjust for purchasing power parity (over countries and time) we obtain data on real per capita income from the latest version of the Penn World Tables, PWT6.1, which have data on real per capita incomes for over 150 countries spanning a 50-year period. The URL for PWT6.1 is http://pwt.econ.upenn.edu/php_site/pwt_index.php. PWT6.1 also provides data on the population size of each of the countries. For each country and for a given year, let $\overline{y}$ be the real per capita income adjusted for differences in prices across countries and over time, and let S be the size of the population. For each income group in a country the real class mean income for income class i, $\overline{y}_i$, is derived as total income in the i-th group, $g_i\,\overline{y}\,S$, divided by total population in the i-th group, $c_i\,S$. That is, $\overline{y}_i = g_i\,\overline{y}/c_i$. Data on c_i and $\overline{x}_i$ are drawn from Milanovic (2002) for 1993 and from WIID2a for 2000. These are used only for determining income shares in each of the decile groups. Data for S and $\overline{y}$ are sourced from PWT6.1. The PWT income data are used to calculate average income $\overline{y}_i$ for the i-th decile group. The values $\overline{y}_i$ and c_i are those used in the later analysis.

3.2 Coverage

This paper covers 91 countries for both 1993 and 2000. The countries covered according to geographical groupings are as follows:

Western Europe, North America and Oceania, WENAO (22 countries)

> Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Luxembourg, The Netherlands, Norway, New Zealand, Portugal, Sweden, United Kingdom, United States, Turkey.

Latin America and the Caribbean (18 countries)

> Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Honduras, Jamaica, Mexico, Panama, Venezuela, Ecuador, Peru, Argentina, El Salvador, Guyana, Nicaragua, Uruguay.

Eastern Europe (17 countries)

> Armenia, Bulgaria, Slovak Republic, Hungary, Romania, Belarus, Estonia, Kazakhstan, Krygyz Republic, Latvia, Lithuania, Moldova, Russia, Ukraine, Uzbekistan, Slovenia, Albania.

Asia (18 countries)

> Bangladesh (both rural and urban), China (both rural and urban), Chinese Taipei, Hong Kong SAR, India (both rural and urban), Indonesia (both

rural and urban), Japan, Jordan, Korea South, Pakistan, The Philippines, Thailand, Iran, Laos, Nepal, Sri Lanka, Vietnam, Yemen.

Africa (16 countries)

Algeria, Egypt, Ghana, Madagascar, Morocco, Nigeria, Tunisia, Uganda, Zambia, Burkina Faso, Ethiopia, The Gambia, Kenya, Mauritania, South Africa, Zimbabwe.

Table 1 reports the percentage coverage for each continent and for the two years. For both years, we cover nearly 90 per cent of the world population. In terms of continents, it can be seen that we cover more than 90 per cent of the total population for Asia, Latin America and the Caribbean and WENAO. The percentage coverage is less for Eastern Europe and Africa. In particular the coverage for the African continent is only about 60 per cent for both years.

Appendix Table A1 compares the country coverage in this paper to those in Milanovic (2002) who covers 86 countries in total. (In some countries Milanovic considers rural and urban separately and each count as one country.) The majority of countries are the same with minor differences.

Sala-i-Martin (2002a, 2002b) investigates global income distributions between 1970 and 1998. He covers 125 countries and classifies them into three groups according to the level of data. Group A includes countries that have some data on country income shares by quintiles over time. Group B includes countries that have only one observation between 1970 and 1998 and Group C includes countries for which there is no data on income shares. He uses income shares for each country in group A to estimate a kernel density for each country and each year. For the treatment of countries in Groups B and C see Sala-i-Martin (2002a). Our study covers most of the countries in Group A and some in Group B. Most of the countries in Eastern Europe that are covered in our study are not covered in Sala-i-Martin's study.

4 Empirical analysis

Our presentation and discussion of the results begins in Section 4.1 with consideration of the estimated country-specific income distributions for eight countries as examples. These eight countries were selected from different continents and because of their different sizes and level of development. They are India, China, USA, Brazil, Egypt, Kenya, Mexico and Russia. Goodness-of-fit of the distributions is assessed in Section 4.2. Levels and trends in inequality are examined in Section 4.3. In Section 4.4 we discuss the regional income distribution and compare regional inequality over the two years.

4.1 Country-specific income distributions and inequality in selected countries

Table 2 shows the estimated parameters of the beta distributions for the example countries. They are obtained using the procedure described in Section 2.1. The estimated parameters provide meaningful income distributions, all of which are skewed and uni-modal. However, the very large values of p and relatively small values of b for

India appear out of place. As found in Chotikapanich, Griffiths and Rao (2007), the parameters b and p were highly correlated and alternative pairs of (b, p) close to the convergence point led to virtually identical income distributions. Also, the best data available for India are in quintile shares. To estimate the parameters of the distribution based on only five data points may result in the estimation being unstable. However, as can be seen later in Section 4.2, that even with only five data points our estimation produces a reasonable goodness-of-fit when actual and estimated income shares are compared.

Figure 1 shows the plots of the density functions for 1993 and 2000. For each year the results are reported in two graphs because of the vast differences in the locations of the density functions for the poorest (Kenya) and the richest country (USA). The density functions, however, are consistent with general expectations. The locations of the distributions in terms of the mode and the mean appear to be ordered according to the real per capita incomes of these countries. Also informative are the distribution functions and Lorenz curves for each country in each of the two years. To find them we select a grid of income points $(y_1, y_2, \ldots, y_L)$ and compute $F(y_i) = B_{y_i/(b+y_i)}\left(p, q\right)$ and $\eta_i = B_{y_i/(b+y_i)}\left(p+1, q-1\right)$. Figures 2a and 2b show the distribution functions for the selected eight countries in the study. These countries appear to be consistently ranked from the poorest to the richest. From 1993 to 2000, the shape and location of the distributions changed but the ranking remained unaltered over the two periods. In terms of dominance, no clear dominance pattern is evident for the cases of Russia, Mexico and Brazil for 1993 and these three countries plus Egypt and China for 2000. For these countries the distribution functions cross at some income levels. Figures 3a and 3b depict the Lorenz curves. These figures show no clear Lorenz ordering.

4.1.1 Goodness-of-fit of beta distributions

It is useful to assess the goodness-of-fit of the beta distributions by comparing the observed income shares with the expected income shares derived using the estimated distributions. The empirical income shares are given by

$$g_i = \frac{c_i\,\bar{y}_i}{\sum_{j=1}^{N} c_j\,\bar{y}_j} = \frac{c_i\,\bar{x}_i}{\sum_{j=1}^{N} c_j\,\bar{x}_j}$$

To find those implied by each beta distribution we began with the population shares c_i, and corresponding cumulative proportions

$$\pi_i = \sum_{j=1}^{i} c_j$$

and then found class limits a_i (not necessarily the same as the previously-estimated class limits) such that

$$B_{a_i/(\hat{b}+a_i)}\left(\hat{p}, \hat{q}\right) = \pi_i$$

Corresponding cumulative income shares were found from the first moment distribution function

$$\hat{\eta}_i = \frac{1}{\hat{\mu}} \int_0^{a_i} y\, f(y)\, dy$$

$$= \frac{1}{\hat{\mu}} \frac{\hat{p}\hat{b}}{\hat{q}-1} B_{a_i/(\hat{b}+a_i)}\left(\hat{p}+1, \hat{q}-1\right)$$

$$= B_{a_i/(\hat{b}+a_i)}\left(\hat{p}+1, \hat{q}-1\right)$$

The estimated income shares are given by

$$\hat{g}_i = \hat{\eta}_i - \hat{\eta}_{i-1}$$

A comparison of the estimated and observed income shares appears in Table 3 for 1993 and Table 4 for 2000. As was also found in Chotikapanich, Griffiths and Rao (2007), the actual (observed) and estimated (expected) income shares are remarkably similar for the selected countries in both years. In most cases the differences are in the third decimal place. This outcome is very encouraging given that the parameters of the distributions have been estimated from limited data, and given that the class limits a_i implied by the estimated parameters, not the a_i giving the 'best fit', were used to compute the expected income proportions.

4.1.2 Temporal analysis of shifts in country income distribution and levels and trends in inequality

Figure 4 shows the change in density functions between 1993 and 2000. For most of the eight countries the density functions seem to shift to the right from 1993 to 2000, except for Egypt and Russia. Mexico shows no significant change.

The levels and trends in inequality can be studied using Gini coefficients and Lorenz curves. Table 2 reports the estimated means and Gini coefficients for the selected countries and the two years. Between 1993 and 2000 income inequality as can be measured by Gini coefficients increases for India, Egypt, USA, Mexico and Russia and decreases for China, Kenya and Brazil. The estimated mean incomes for all countries increases except for Russia.

In addition to a comparison of the Gini coefficients, Lorenz dominance properties of the estimated income distributions for the years 1993 and 2000 can be examined using a sufficient condition described in Section 2.4. Comparing estimated values of p and q for the years 1993 and 2000 shows that the distribution in 2000 Lorenz dominates (lies completely above or equal to) 1993 for only Kenya. The distributions in 1993 Lorenz dominates 2000 for India, Egypt, and Mexico. The sufficient condition is not satisfied for China, USA, Brazil and Russia. It is also possible to use this condition to assess Lorenz dominance across countries for given time periods. For example, India $\leq_L$ Egypt $\leq_L$ China $\leq_L$ Mexico for 1993 and for 2000 India $\leq_L$ Kenya and China $\leq_L$ Egypt $\leq_L$ Mexico $\leq_L$ Brazil. These dominance properties can also be observed in Figure 3.

4.2 Regional distributions and inequality

4.2.1 Regional density and distribution functions

Figures 5 and 6 are plots for regional and global density functions for 1993 and 2000, respectively. They are obtained as weighted averages of the density functions for each country in the region, and globally. Consider regional distributions first. All regional distributions for both years exhibit unimodal income distributions. As expected, regions with low per capita income have highly skewed distributions, especially Africa and Asia, whereas Latin America and the Caribbean, Eastern Europe and WENAO exhibit less skewed distributions. Figures 7 and 8 show the regional and global income distributions for 1993 and 2000, respectively. It can be seen there is clear dominance for Africa, Asia and WENAO for both years where Asia dominates Africa and WENAO dominates Asia and Africa. However, the same cannot be said for Eastern Europe and Latin America and the Caribbean.

4.2.2 Trends in regional density functions

Figure 9 presents the trends for regional density functions between 1993 and 2000. It can be seen that between these two years the density functions for Asia, Eastern Europe and WENAO move to some extent to the right while that for Latin America and the Caribbean does not exhibit any change. The income distribution for Africa moves slightly but unexpectedly to the left. This is consistent with the reduction in the estimated mean incomes reported in Table 2.

4.2.3 Regional income inequality

Table 5 presents regional and global income inequality for all regions and for 1993 and 2000. The income inequalities are measured by the Gini coefficient and the Theil index. Table 5 also presents the decomposition of inequality in terms of both Gini and Theil indices. Consider first regional income inequality: The regional rankings of income inequality for both years are generally the same, ranging from Africa having the highest inequality followed by Asia to WENAO with the least inequality. These rankings are consistent using both the Gini and Theil measures, except for 1993 where Asia and Latin America and the Caribbean have reverse rankings. In terms of decomposition, Table 5 also reports the percentage contributions of inequality alongside the inequality contributed from within and between countries for the case of Theil indices and interaction or overlapping of the distributions between countries in the region for the case of Gini coefficients. Consider first 1993: For Asia and Africa, as measured by Gini coefficients, and for both years, the majority of total inequality (around 70.72 per cent for Asia and 76.36 per cent for Africa) is contributed from the inequality in income between countries in the regions. This result is not unexpected since there are very rich and very poor countries in these two regions. Moreover, the inequalities contributed by the interaction terms in these two regions are also low, around 16 per cent in 1993 and 19 per cent for 2000, suggesting that the degree of overlapping in the distributions between countries is not very high. The contribution of inequality between countries is between 28.55 to 36.78 per cent for LAC, EE and WENAO with higher percentage contribution to inequality from interaction terms between 35.65 per cent for EE to 49.50 per cent for LAC. Overall, the regional inequality decomposition picture as measured by Gini coefficients for the year 2000 is similar.

4.3 Global income distribution

4.3.1 Global density functions for 1993 and 2000

Consider the global density functions in Figures 5 and 6: It can be seen that the global income density function changes from 1993 and exhibits some degree of bimodality in 2000. (It can also be seen in Figure 10 which shows the change in the global density function between 1993 and 2000.) The apparent reason for the first mode towards the left tail of the 2000 curve is because Africa is relatively poor. The first mode of the global density function at the left tail seems to coincide with the spike of the African density curve. Another interesting outcome in Figures 5 and 6 is that density functions for all regions seem to move from 1993 outward to the right in 2000 except for Africa. This means that all the regions are better off in 2000 (as can also be seen by the increase in mean incomes in Table 2) except Africa. The African region seems to be left behind.

4.3.2 Trends in global income distributions and income inequality

Table 5 presents global income inequality for 1993 and 2000 alongside regional income inequality. Global inequality, as measured by the Gini coefficient, decreases from 0.6404 in 1993 to 0.6291 in 2000. This can also be seen from Figure 11 which exhibits the change in the global Lorenz curve between the two years. In Table 5, the Theil index reduces from 0.8133 in 1993 to 0.7957 in 2000. Both measures indicate that inequality between countries is the major contribution to the total inequality. Hence, policies toward reducing global inequality should give priority to catching up between countries.

Table 6 presents global income distributions for the two years in terms of cumulative percentage of persons and incomes. The poorest 50 per cent of the population earns 9.5 per cent and 10.3 per cent of total income for 1993 and 2000, respectively. The top richest 10 per cent of the population earns about 50 per cent of the total income. There is a slight change in the distributions between the two years with population in the top of the distribution earning slightly more in 2000.

Table 5 also presents some interesting links in the characteristics of global and regional income inequality. At the global level, inequality decreases from 0.6404 in 1993 to 0.6291 in 2000. At the regional level, the only region in which inequality decreases is Asia. Inequality in Africa increases significantly while those in WENAO, EE and LAC increase only slightly. It is not surprising that global inequality decreases when inequality in Asia decreases since, for the countries considered in this study, the Asian population makes up 61.62 per cent of the global population. If we look further into income inequality in Asia we find the major contribution to total inequality is from inequality between countries. However, there is some evidence that the percentage contribution of inequality between countries decreases between 1993 and 2000 suggesting catch-up and convergence between countries in Asia. Table 7 examines global inequality further, looking at the contributions from including China and India in the analysis. In this table we recalculate global inequality by leaving out first China and then India separately and then both at the same time. It is found that without China global inequality increases and without India global inequality decreases. Without both China and India, global inequality increases. Since the populations of China and India contribute nearly half of global population, we can conclude that the biggest impact on the reduction of global inequality between the two years is from the fast growth in China that results in it catching-up with the rest of the world.

5 Summary and conclusions

In summary, the results reported in this paper show a very high but reducing degree of inequality at the global level. An encouraging feature observed is the catch-up and convergence between countries. In particular, it is evident that the reduction in global inequality is due to the catching up between China and the world which is a consequence of the fast economic growth in China.

Table A1: Countries included in the study

	Common countries	Milanovic (86)	This paper (91)
Western Europe, North America and Oceania		22	22
	Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Luxembourg, The Netherlands, Norway, New Zealand, Portugal, Sweden, United Kingdom, United States	Switzerland	Turkey
Latin America and the Caribbean		17	18
	Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Honduras, Jamaica, Mexico, Panama, Venezuela, Ecuador, Peru	Argentina (u), El Salvador (u), Paraguay, Uruguay (u)	Argentina, El Salvador, Guyana, Nicaragua, Uruguay
Eastern Europe		22	17
	Armenia, Bulgaria, Slovak Republic, Hungary, Romania, Belarus, Estonia, Kazakhstan, Krygyz Republic, Latvia, Lithuania, Moldova, Russia, Ukraine, Uzbekistan, Slovenia	Czech Republic, East Germany, Georgia, Poland, Turkmenistan, Yugoslavia	Albania
Asia		13	18
	Bangladesh (r) (u), China (r) (u), Chinese Taipei, Hong Kong SAR, India (r) (u), Indonesia (r) (u), Japan, Jordan, Korea South, Pakistan, Philippines, Thailand	Malaysia	Iran, Laos, Nepal, Sri Lanka, Vietnam, Yemen
Africa		12	16
	Algeria, Egypt (r) (u), Ghana, Madagascar, Morocco, Nigeria, Tunisia, Uganda, Zambia	Ivory Coast, Lesotho, Senegal	Burkina Faso, Ethiopia, The Gambia, Kenya, Mauritania, South Africa, Zimbabwe

Note: r = rural, u= urban

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Table 1

World population (in millions)

	World population		Population included in the study			
	1993	2000	1993	%	2000	%
Africa	672	813	417	62.1	482	59.3
Asia	3,206	3,628	3,006	93.8	3,302	91.0
Eastern Europe	411	365	322	78.3	317	86.9
Latin America and the Caribbean	462	523	424	91.8	473	90.4
WENAO	755	758	710	94.0	746	98.4
World	5,506	6,087	4,878	88.6	5,320	87.4

Note: 1993 population figures are from Milanovic (2002). The 2000 figures are based on the report by Population Section at the United Nations. The Web page is: http://esa.un.org/unpp/

Table 2

Estimated coefficients from beta distributions

	1993	2000		1993	2000
India			Egypt		
b	0.1802	2.0531	*b*	471.35	1165.81
p	29923.17	2571.69	*p*	15.4063	3.8923
q	3.9277	3.1879	*q*	3.0786	2.0864
mean	1770.71	2407.29	mean	3492.07	4160.55
Gini	0.3159	0.3604	Gini	0.3923	0.5432
China			Kenya		
b	1260.25	1474.86	*b*	208.66	91.51
p	4.3622	5.6155	*p*	4.4013	18.8845
q	2.9544	3.5293	*q*	1.7355	2.3919
mean	2455.17	3747.50	mean	1240.68	1242.96
Gini	0.4522	0.4039	Gini	0.6018	0.4538
USA			Mexico		
b	181432.60	60879.06	*b*	2089.20	2741.33
p	2.0009	2.6443	*p*	4.0059	3.3497
q	14.0315	5.7531	*q*	2.1187	2.0433
mean	26927.54	33835.94	mean	7480.08	8830.25
Gini	0.4022	0.4093	Gini	0.5373	0.5588
Brazil			Russia		
b	4606.08	2516.05	*b*	69017.02	10672.19
p	1.5108	2.4007	*p*	1.9712	2.6457
q	2.1061	1.8474	*q*	16.6886	4.4816
mean	6265.93	7104.14	mean	8665.62	8126.81
Gini	0.6111	0.6105	Gini	0.4001	0.4322

Table 3

Income shares 1993

Egypt actual	Egypt estimated	Kenya actual	Kenya estimated	China actual	China estimated	India actual	India estimated
0.027	0.027	0.012	0.011	0.019	0.018	0.088	0.087
0.040	0.039	0.015	0.019	0.031	0.031	0.125	0.125
0.049	0.049	0.028	0.026	0.039	0.041	0.162	0.163
0.057	0.058	0.036	0.034	0.049	0.051	0.214	0.219
0.067	0.068	0.045	0.043	0.060	0.062	0.411	0.406
0.080	0.080	0.057	0.055	0.076	0.076		
0.097	0.096	0.071	0.071	0.096	0.093		
0.117	0.118	0.093	0.096	0.125	0.119		
0.155	0.155	0.139	0.145	0.169	0.162		
0.310	0.309	0.503	0.501	0.337	0.347		

Russia actual	Russia estimated	Brazil actual	Brazil estimated	Mexico actual	Mexico estimated	USA actual	USA estimated
0.015	0.015	0.005	0.005	0.013	0.013	0.015	0.015
0.032	0.031	0.015	0.014	0.023	0.023	0.033	0.031
0.046	0.045	0.024	0.023	0.032	0.032	0.046	0.045
0.059	0.058	0.034	0.033	0.041	0.041	0.059	0.058
0.073	0.073	0.044	0.044	0.051	0.051	0.073	0.072
0.088	0.089	0.057	0.058	0.064	0.064	0.088	0.088
0.106	0.108	0.073	0.076	0.081	0.082	0.105	0.108
0.132	0.134	0.100	0.105	0.107	0.108	0.129	0.133
0.173	0.172	0.154	0.158	0.155	0.157	0.167	0.172
0.277	0.275	0.494	0.484	0.431	0.429	0.285	0.277

Table 4

Income shares 2000

Egypt		Kenya		China		India	
actual	estimated	actual	estimated	actual	estimated	actual	estimated
0.012	0.013	0.023	0.023	0.024	0.023	0.032	0.032
0.024	0.023	0.033	0.033	0.035	0.036	0.044	0.044
0.033	0.031	0.040	0.042	0.046	0.047	0.053	0.053
0.042	0.040	0.050	0.051	0.057	0.057	0.061	0.062
0.052	0.051	0.060	0.060	0.069	0.068	0.071	0.071
0.063	0.063	0.070	0.073	0.082	0.081	0.082	0.082
0.078	0.081	0.100	0.089	0.099	0.098	0.097	0.097
0.101	0.107	0.112	0.112	0.123	0.121	0.118	0.117
0.146	0.156	0.151	0.154	0.162	0.160	0.154	0.152
0.448	0.435	0.361	0.364	0.304	0.308	0.289	0.290

Russia		Brazil		Mexico		USA	
actual	estimated	actual	estimated	actual	estimated	actual	estimated
0.014	0.016	0.008	0.008	0.011	0.012	0.018	0.018
0.034	0.030	0.016	0.016	0.021	0.021	0.035	0.033
0.046	0.042	0.024	0.024	0.030	0.029	0.048	0.045
0.058	0.054	0.032	0.032	0.039	0.038	0.060	0.057
0.069	0.067	0.042	0.042	0.049	0.049	0.073	0.070
0.083	0.082	0.052	0.055	0.063	0.062	0.087	0.085
0.097	0.100	0.070	0.072	0.079	0.079	0.103	0.103
0.118	0.126	0.098	0.100	0.104	0.106	0.125	0.128
0.154	0.168	0.157	0.152	0.155	0.156	0.161	0.168
0.326	0.315	0.500	0.498	0.448	0.448	0.290	0.294

Note**:** All shares are decile shares with the exception of India and Brazil for 1993 where the population proportions were not equal for each class. Brazil has ten classes and India has five classes.

Table 5

Global and regional income inequality

			Global		Asia		WENAO		Africa		EE		LAC	
	countries		91		18		22		16		17		18	
1993	Pop (%)		4878408000	100.00	3005884000	61.62	709695000	14.55	416951800	8.55	322098800	6.60	423778400	8.69
	mean		6357.48		3377.76		21017.56		2308.07		7060.67		6391.54	
	Gini		0.6404	100.00	0.5607	100.00	0.3959	100.00	0.5921	100.00	0.4247	100.00	0.5347	100.00
		within	0.0215	3.36	0.0712	12.70	0.0798	20.16	0.0459	7.74	0.1193	28.09	0.1174	21.95
		between	0.5405	84.40	0.3965	70.72	0.1456	36.78	0.4521	76.36	0.1540	36.26	0.1527	28.55
		interaction	0.0784	12.24	0.0930	16.59	0.1705	43.07	0.0941	15.90	0.1514	35.65	0.2647	49.50
	Theil		0.8133	100.00	0.5468	100.00	0.3008	99.99	0.7340	100.00	0.3324	100.00	0.6104	100.00
		within	0.2882	35.44	0.2537	46.40	0.2401	79.81	0.3583	48.81	0.2657	79.93	0.5615	91.99
		between	0.5251	64.56	0.2931	53.60	0.0607	20.18	0.3757	51.19	0.0667	20.07	0.0489	8.01
2000	Pop (%)		5319485000	100.00	3302017000	62.07	746004100	14.02	482216000	9.07	316743000	5.95	472505600	8.88
	mean		7477.37		4293.86		25365.26		2439.35		6701.96		7144.25	
	Gini		0.6291	100.00	0.5350	100.00	0.3976	100.00	0.6449	100.00	0.4389	100.00	0.5413	100.00
		within	0.0239	3.80	0.0761	14.22	0.0846	21.29	0.0483	7.50	0.1211	27.58	0.1201	22.19
		between	0.5247	83.40	0.3576	66.84	0.1681	42.28	0.4748	73.63	0.1774	40.42	0.1585	29.28
		interaction	0.0805	12.80	0.1013	18.93	0.1449	36.43	0.1217	18.87	0.1404	32.00	0.2627	48.53
	Theil		0.7957	100.00	0.4903	100.00	0.3085	100.00	0.9063	100.00	0.3638	100.01	0.6643	100.00
		within	0.3031	38.09	0.2491	50.81	0.2322	75.27	0.4827	53.26	0.2957	81.28	0.6121	92.14
		between	0.4926	61.91	0.2412	49.19	0.0763	24.73	0.4236	46.74	0.0681	18.73	0.0522	7.86

Table 6

Global income distribution

Cumulative percentage of persons and income		
Cumulative percentage of persons	Cumulative percentage of income	
	1993	2000
Bottom		
10	0.8	0.7
20	2.1	2.2
50	9.5	10.3
75	24.0	25.0
85	38.1	38.1
Top		
10	50.0	50.9
5	33.1	34.7
1	11.4	12.5

Note: calculated from the estimated global distribution functions

Table 7

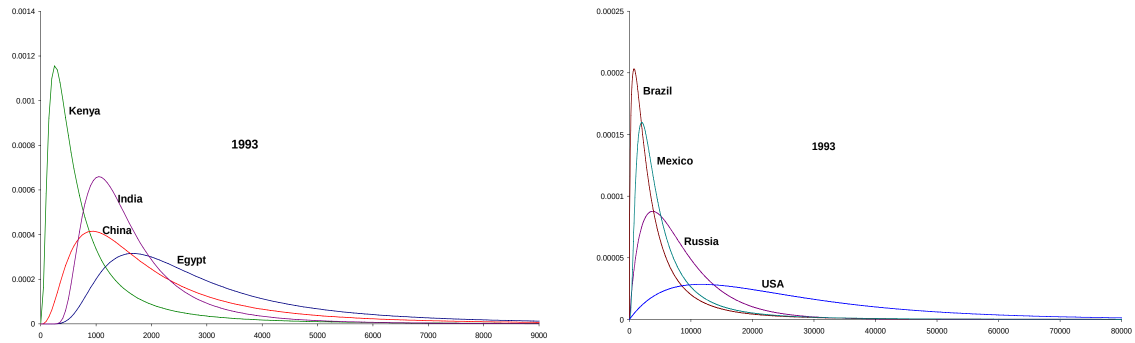
Global income inequality

			Global		Global without China		Global without India		Global without China and India	
	countries		91		90		90		89	
	Pop (%)		4878408000	100.00	3700006000	75.84	3980208000	81.59	2801806000	57.43
1993	mean		6357.48		7600.32		7392.56		9469.17	
	Gini		0.6404	100.00	0.6345	100.00	0.6302	100.00	0.6021	100.00
		within	0.0215	3.36	0.0165	2.60	0.0240	3.80	0.0170	2.83
		between	0.5405	84.40	0.5396	85.04	0.5215	82.75	0.4866	80.81
		interaction	0.0784	12.24	0.0784	12.36	0.0847	13.45	0.0985	16.36
	Theil		0.8133	100.00	0.8351	100.00	0.8228	100.00	0.8039	100.00
		within	0.2882	35.44	0.2672	32.00	0.3169	38.51	0.3012	37.46
		between	0.5251	64.56	0.5679	68.00	0.5060	61.49	0.5027	62.54
	Pop (%)		5319485000	100.00	4060664000	76.34	4303562000	80.90	3044741000	57.24
2000	mean		7477.37		8633.65		8674.24		10711.16	
	Gini		0.6291	100.00	0.6434	100.00	0.6227	100.00	0.6227	100.00
		within	0.0239	3.80	0.0187	2.90	0.0259	4.16	0.0177	2.85
		between	0.5247	83.40	0.5488	85.29	0.5113	82.11	0.5132	82.41
		interaction	0.0805	12.80	0.0760	11.81	0.0855	13.73	0.0918	14.74
	Theil		0.7957	100.00	0.8863	100.00	0.8146	100.00	0.9009	100.00
		within	0.3031	38.09	0.3113	35.12	0.3247	39.86	0.3445	38.24
		between	0.4926	61.91	0.5750	64.88	0.4899	60.14	0.5563	61.76

Figure 1

Density functions for selected countries: (a) 1993, (b) 2000

(a)



(b)

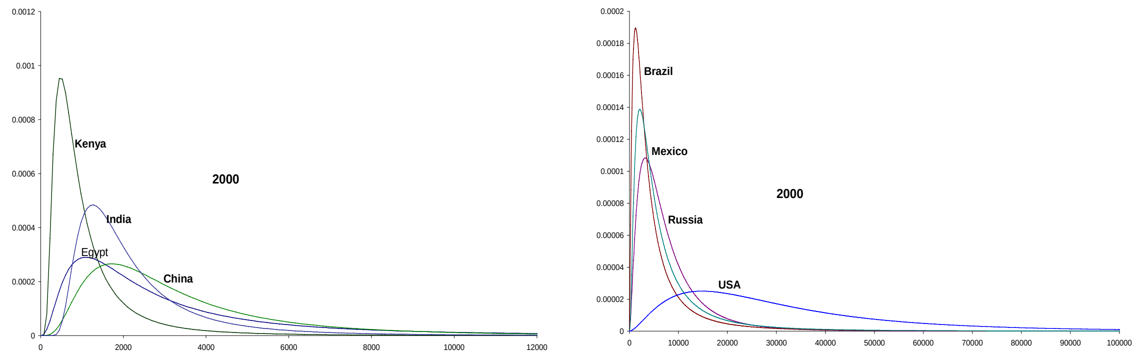
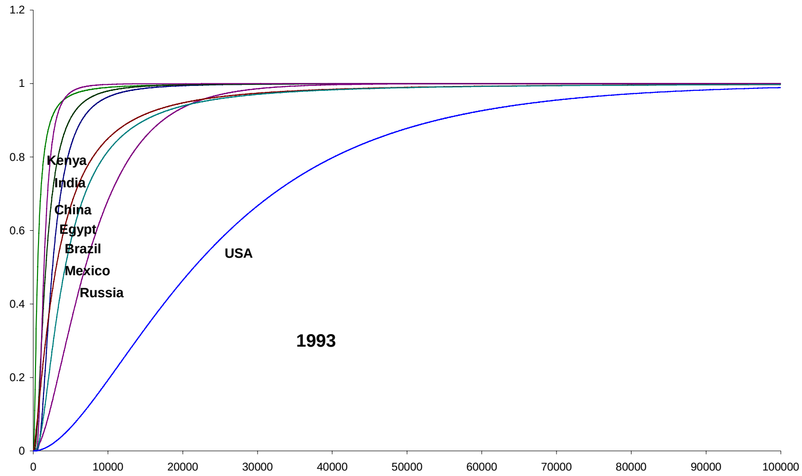


Figure 2

Distribution functions for selected countries: (a) 1993, (b) 2000

(a)



(b)

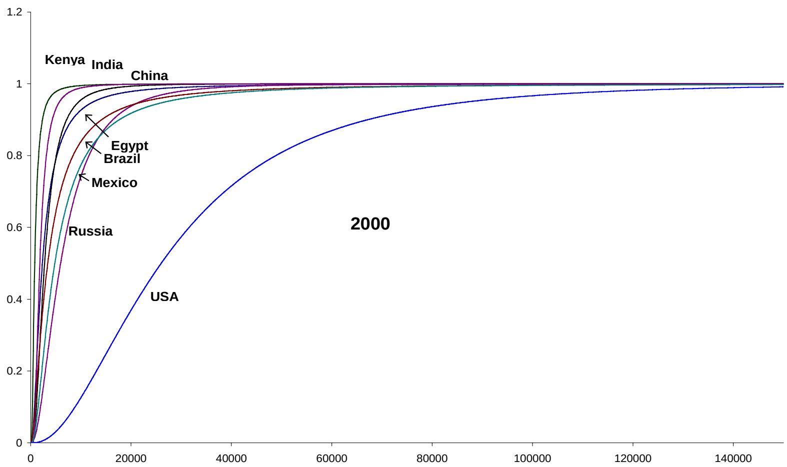
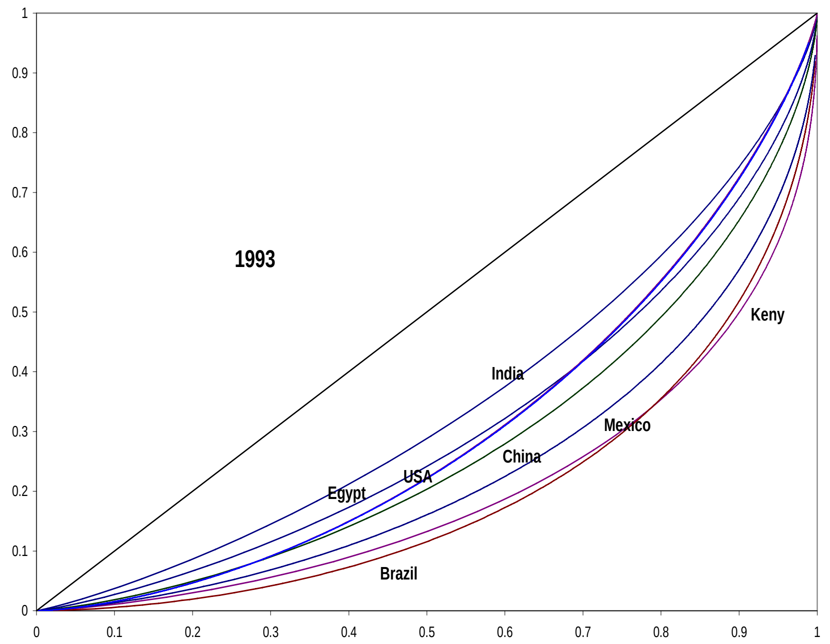


Figure 3
Lorenz curves for selected countries: (a) 1993, (b) 2000

(a)



(b)

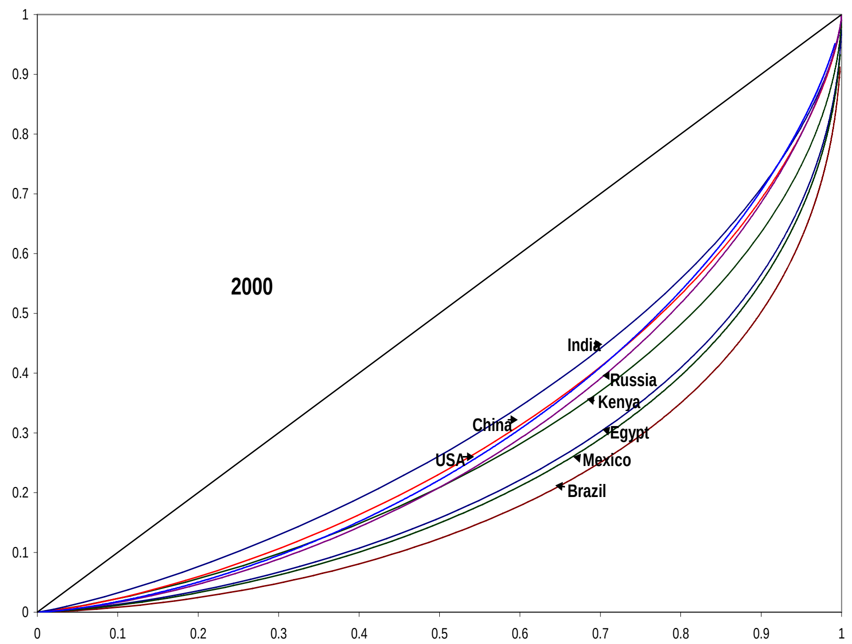


Figure 4

Country-specific density functions between 1993 and 2000

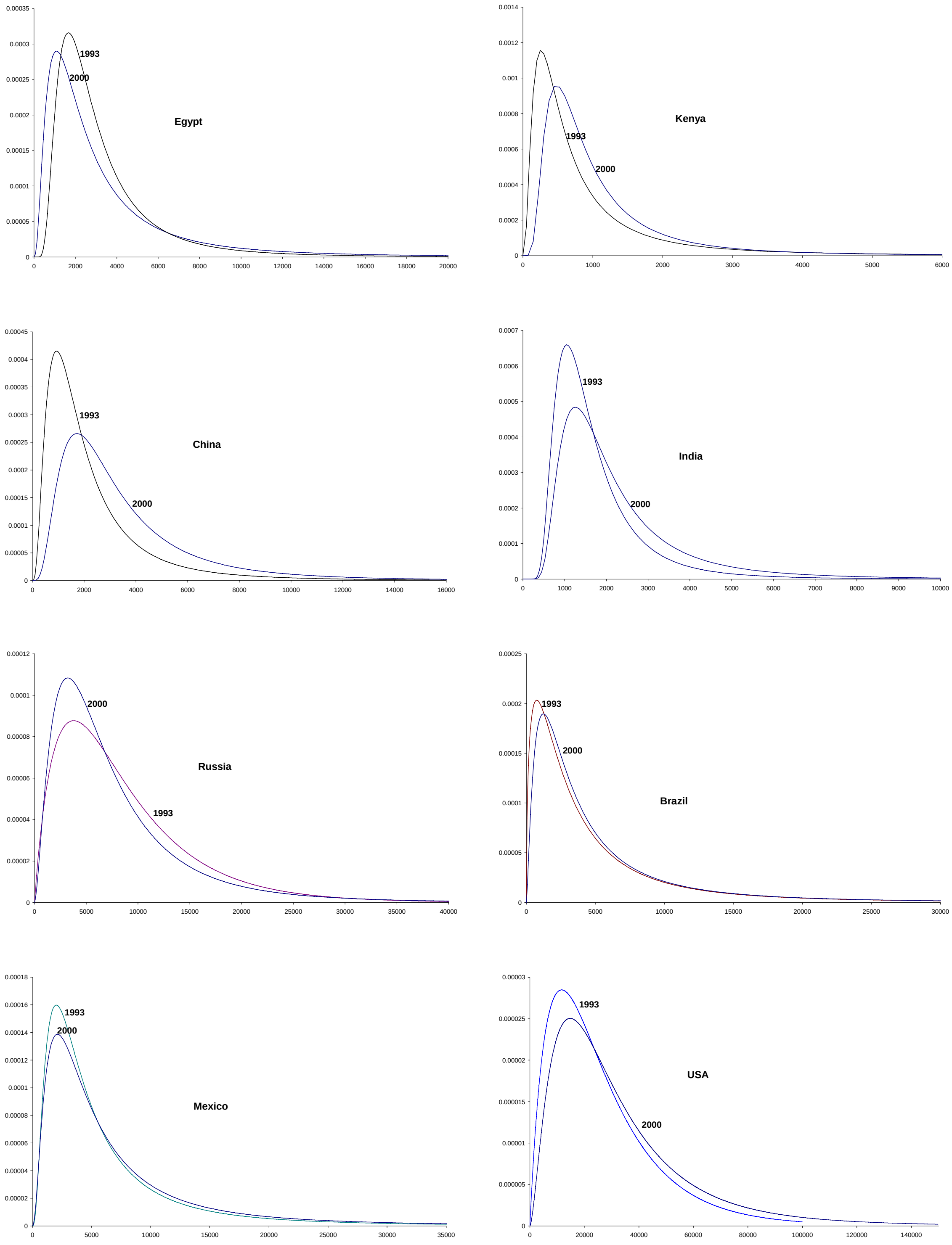


Figure 5

Regional and global density functions

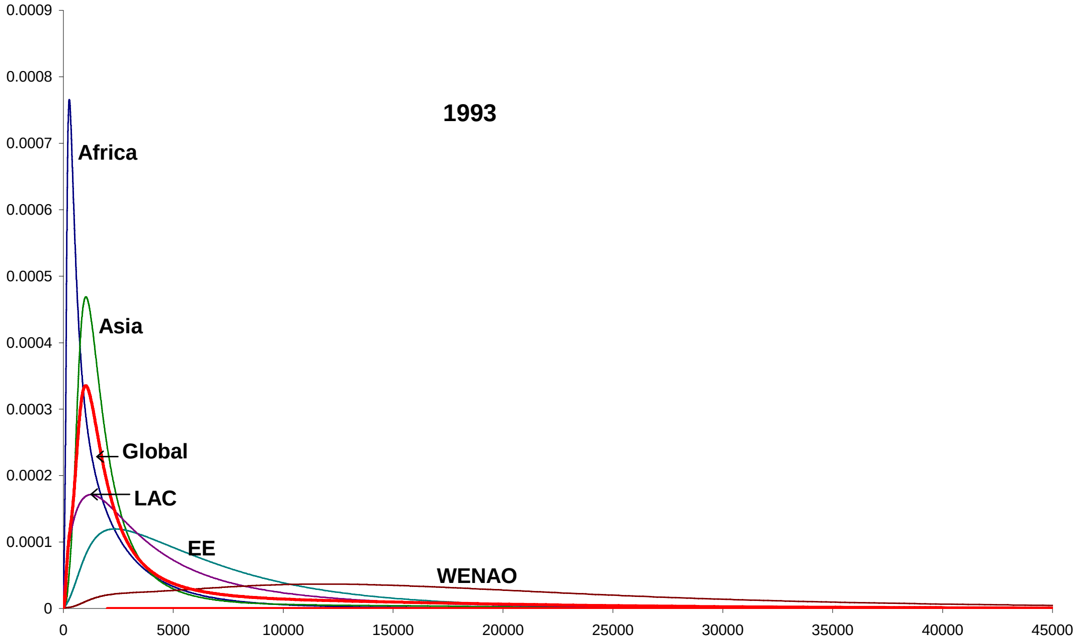


Figure 6

2000 Regional and global density functions

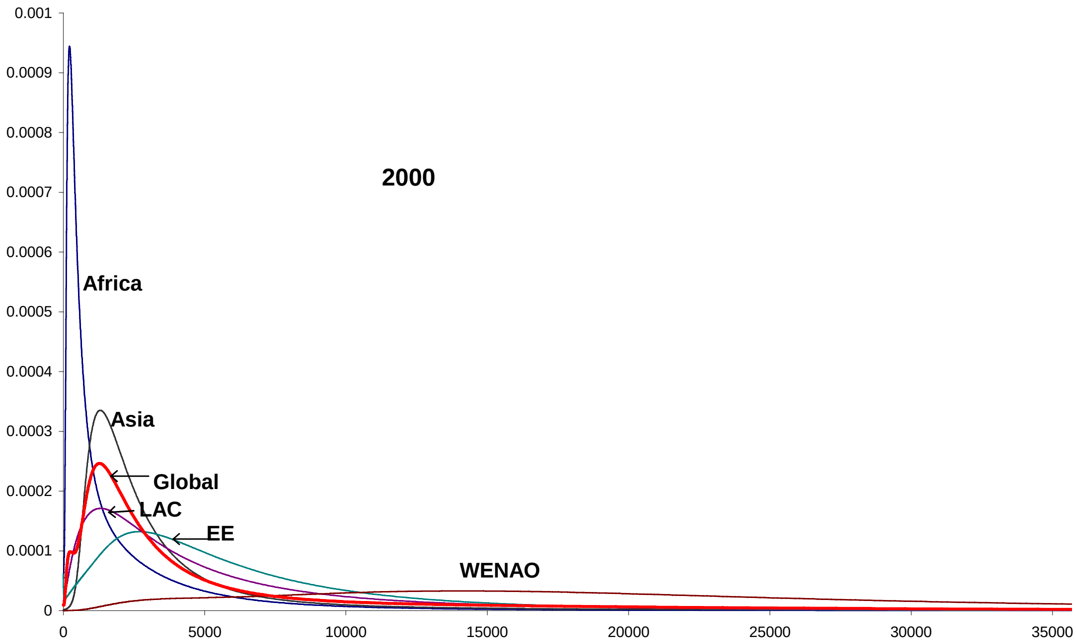


Figure 7

1993 Regional and global distribution functions

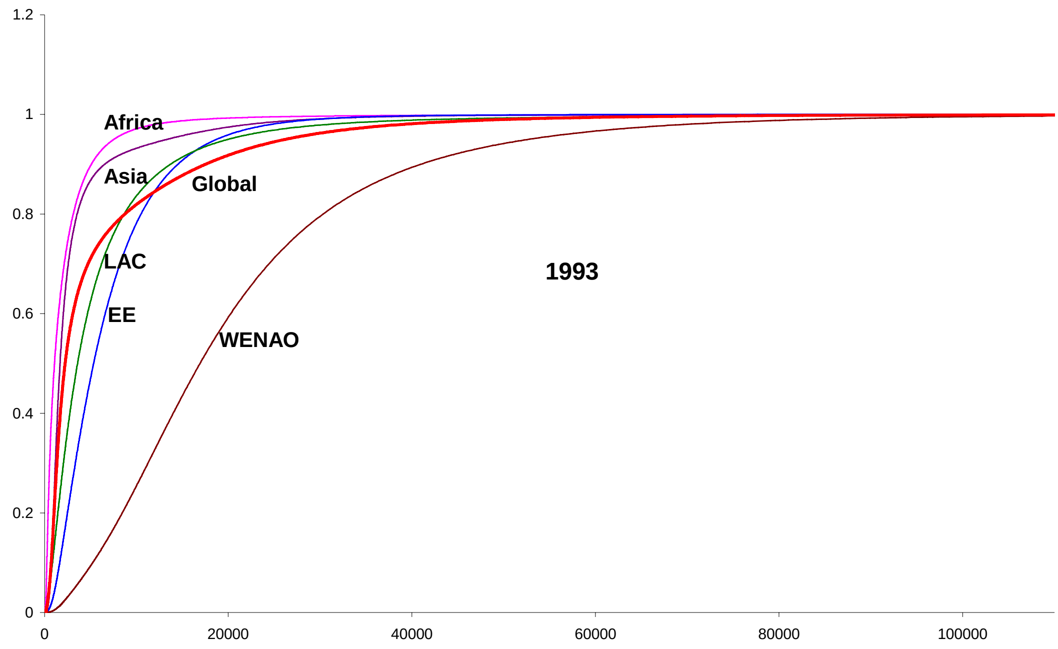


Figure 8

2000 Regional and global distribution functions

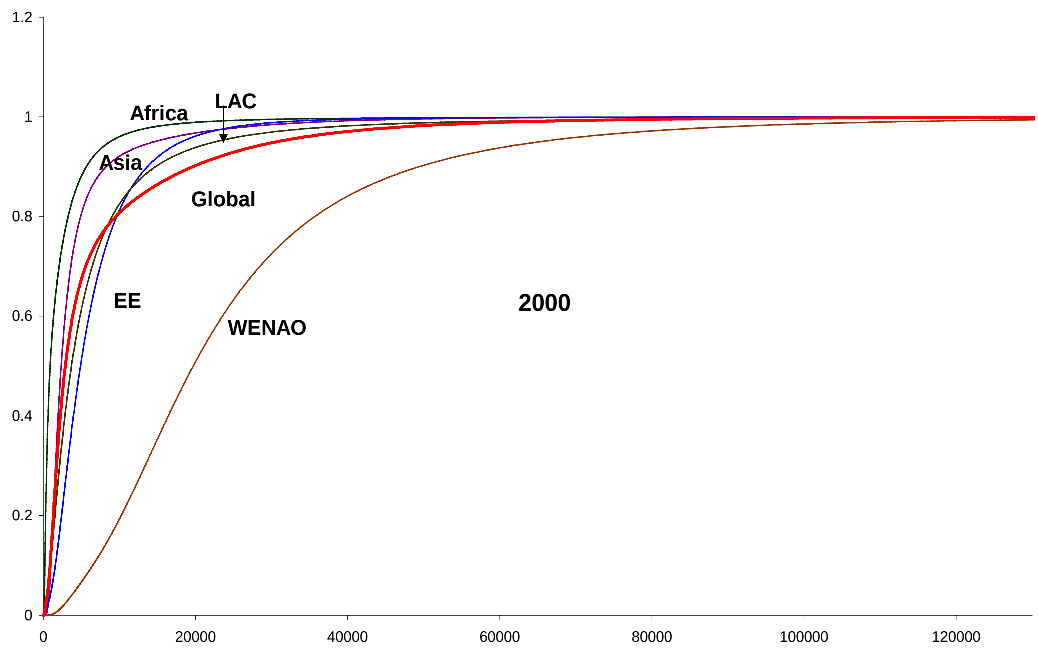


Figure 9

Regional density functions over time

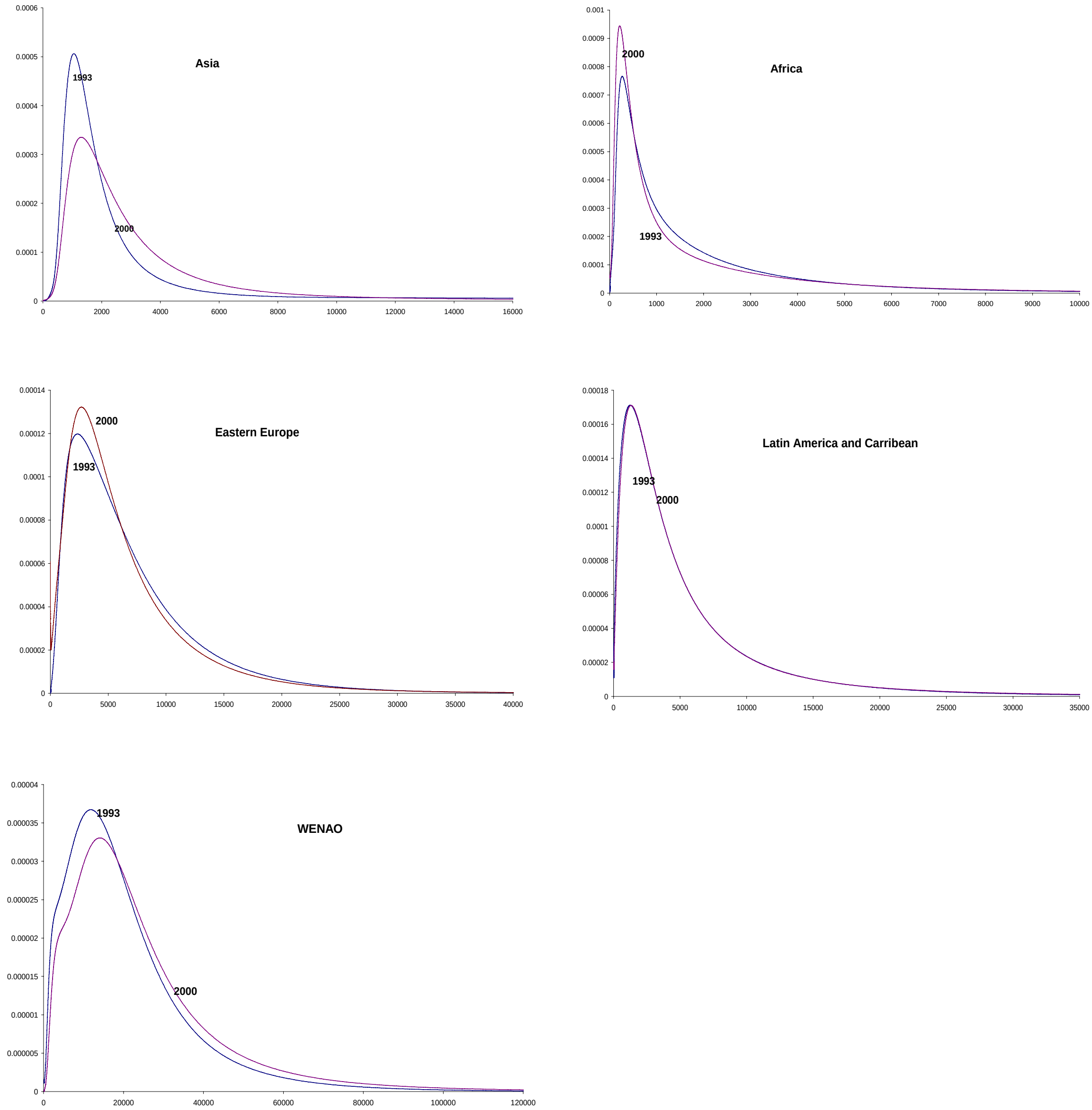


Figure 10

Global density functions

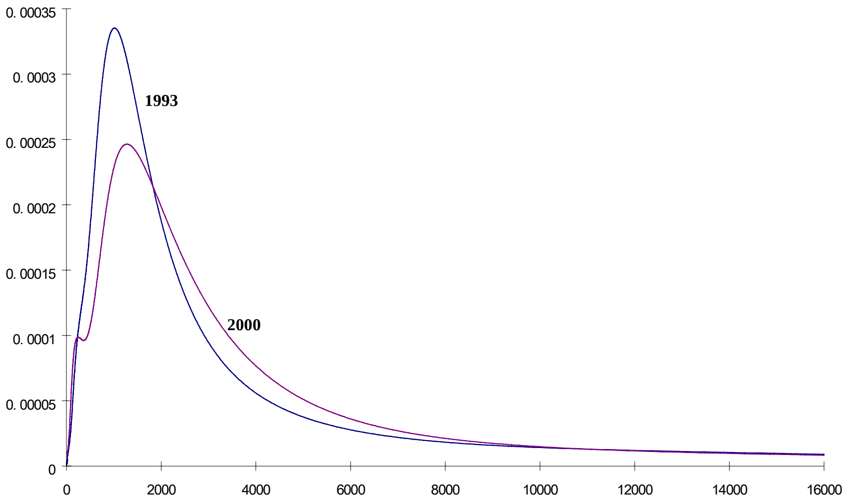


Figure 11

Global Lorenz curves