



*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

*No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.*



**Global Trade Analysis Project**

<https://www.gtap.agecon.purdue.edu/>

This paper is from the  
GTAP Annual Conference on Global Economic Analysis  
<https://www.gtap.agecon.purdue.edu/events/conferences/default.asp>

# Will Incomes around the World Converge or Diverge? The Prospects for Global Income Inequality

Maurizio Bussolo      Rafael E. De Hoyos\*

Denis Medvedev

Development Prospects Group, The World Bank

June 6, 2007

## 1 Introduction

With the increasing pace at which domestic markets are becoming integrated into a common global system, the debate on income disparities around the world has intensified. By creating global awareness, globalization had placed people's own perception of wellbeing within an international context giving more relevance to the concept of global income distribution (Milanovic 2006). The common understanding is that the recent globalization process has exacerbated inequalities between rich and poor *countries* and between poor and rich *individuals* within the countries. The literature, nevertheless, does not provide an unambiguous support for this statement. Bourguignon and Morrisson (2002) show that during the last 30 years the global income distribution experienced very little changes, Sala-i Martin (2006) argues that global disparities had reduced in the last years, and on a diametrically opposing view, Milanovic (2002) shows that the global distribution deteriorated between 1988 and 1993.<sup>1</sup>

---

\*Corresponding author: Development Prospects Group, The World Bank, 1818 H Street Washington, DC., email address: rdehoyos@worldbank.org

<sup>1</sup>Most of the discrepancies in the trends in global income distribution arise from the differences in data sources, country/year coverage, and the way in which different studies impute missing data. Bourguignon and Morrisson (2002) and Sala-i Martin (2006) use GDP per capita as the measure of average incomes across countries whereas Milanovic (2002) use the mean income reported by household survey data.

One of the few consensus found in the literature is that more than half (around 70 percent) of the total income disparities among all individuals in the world are explained by differences on average incomes across countries. The importance of average incomes across countries in explaining global disparities places the convergence literature at the heart of the global income distribution debate (Quah 1996). This does not mean that inequalities at the national level are to be dismissed. In fact, by ignoring intra-country income inequality we can arrive to a completely different understanding about the levels and trends of global inequality (Milanovic 2002). Therefore, the evolution on the income gap between, say, a British and a Chinese citizen will depend on GDP growth in Britain and China as well as the changes in the distribution within these two countries.

The objective of this paper is to project the global income distribution by means of changes in growth rates across countries and income inequality within them. The present study represents the first attempt to analyze the prospects for global income distribution. We develop a novel framework for Global Income Distribution Dynamics (GIDD) which combines a computable general equilibrium (CGE) model with a micro-simulation system at the global level. The global CGE computes income growth rates which are then used to shock incomes at the household level obtaining the *convergence* component of changes in global inequality, i.e. changes in global distribution due to changes in average incomes between countries keeping within-country inequality constant. Our analysis is not limited to changes in average incomes across countries; using a newly developed global household income dataset, we are able to explore the effects of changes in global disparities attributable to changes in within-country inequality (*dispersion* component).<sup>2</sup> Our framework uses the CGE-consistent changes in skilled-to-unskilled wage premium in rural and urban areas to modify incomes at the household level. These changes in skill premiums create a new distribution of incomes within each country. Within the GIDD's framework, an ex-ante change in the global income distribution is the outcome of changes in average incomes *between* countries and changes in income inequality *within* them. The analysis allows us to understand how changes in global income distribution are accounted for by changes in growth rates across countries and changes in income differences within national states. This study represents a big jump in our understanding of global income inequality estimating, for the first time, a global Macro-Micro model.

---

<sup>2</sup>A new dataset was assembled as part of the GIDD project. The new dataset as well as a paper documenting the steps followed to construct it is available from (place GIDD's webpage link here)

According to WorldBank (2006), in the next 20 years the developing world will enjoy rates of growth higher than those experienced by rich countries, therefore, the income of citizens in poor countries will tend to converge slowly towards the levels observed in high-income countries. WorldBank (2006) also argues that global market integration is a fundamental component behind the coming global growth. It is therefore expected to see a world-wide redistribution of resources creating winners and losers within countries as a result of the forthcoming globalization. We use the GIDD framework to uncover the global distributional consequences of the next wave of growth and globalization. Using household survey data for 83 countries and grouped income data for 32 countries covering 91 percent of the world's population (see Annex 1 for details), we project the global income distribution for year 2030.

The paper is organized in the following way. The next section discusses the contributions on global income distribution identifying the sources behind the debate about its recent trends. Section 3 develops a model for Global Income Distribution Dynamics (GIDD) which is then used to undertake ex-ante simulations of global inequality. A brief description of the data and the results are presented in Section 4. In this section we use the GIDD to project the global income distribution for 2030; we decompose the total change in inequality into the effects due to changes in between-country average incomes and changes explained by shifts in within-country inequality. Finally Section 5 concludes.

\*\*\* We should talk more about the data in the introduction. The motivation behind the prospects of global income distribution is not yet well justified. Are we including poverty?? \*\*\*

## **2 Are Incomes Around the World Becoming More Unequal?**

Assessing what has happened to global income distribution in the last two decades- and what will happen in the next 25 years- presents a number of challenges. Part of the difficulty lies with choosing an appropriate measure of inequality to capture income disparities around the world. The literature identifies three main approaches to measuring income inequality around the world, all of which have strengths, but each

of which measures a slightly different thing.<sup>3</sup>

1. *Intercountry inequality* is a concept favored by macroeconomists. It measures relative movements across countries and gives each country an equal weight in the world distribution (that is, population size does not matter). This literature tends to conclude that in the last two decades, income distribution has become more unequal.
2. *International inequality* takes into account the relative sizes of countries (that is, results are population-weighted). Its proponents (such as Theil and Seale 1994) point out that failing to use population weights will cause, for example, the fast growth of China to be exactly offset by the anemic growth rates of Malawi or Honduras, even though the number of Chinese citizens who experienced improvements in their incomes far exceeds the populations of either of the other two countries.<sup>4</sup> The broad consensus in this literature is that income inequality has decreased, although this finding is mostly driven by the fast growth in China and India.<sup>5</sup>
3. *Global inequality*, which compares individual incomes regardless of country of citizenship, is a fairly recent concept (Milanovic 2002). Global inequality takes into account within-country inequality, which is ignored by the international inequality approach, where each individual is deemed to earn the country's average income. To a large extent, fast growth in the large emerging economies tends to offset the increases in inequality within countries (see Bussolo et al. (2007)); therefore by this measure, global inequality has remained roughly constant since the late 1980s.

Even though these three methodologies can yield quite different pictures of past and future trends, and none is clearly preferable to the others (Ravallion 2004), it is worth elaborating on some general trends.<sup>6</sup>

---

<sup>3</sup>In this discussion the authors have adopted the naming conventions of WorldBank (2005). Milanovic (2005) refers to the following different measurements as inequality concepts 1, 2, and 3.

<sup>4</sup>Bourguignon, Levin, and Rosenblatt (2004) point out that using the intercountry concept may represent an implicit welfare judgment, whereby the rising incomes of more populous countries cannot offset the losses of smaller countries when their incomes are falling.

<sup>5</sup>The influence of China and India is so large that omitting these two countries would reverse the conclusion: international inequality excluding China and India has increased in the past two decades ((?)).

<sup>6</sup>It should also be noted that measurement of inequality is sensitive to both the precise indicators used to measure it and the time horizon chosen.

Intercountry measurements of inequality suggest that the last five decades of development have done little to bring the average incomes of developing countries closer to those of the countries of the Organisation for Economic Co-operation and Development (OECD). For example, Quah (1996, 1997) finds “emerging twin peaks” in the global distribution, supporting the argument that the relative distance between the top and the bottom of the global income distribution has increased since the 1950s. More generally, Pritchett (1997) has concluded that a “big time” divergence in incomes occurred between 1870 and 1990, evidenced by a doubling of the gap between the per capita incomes of the rich and poor countries.<sup>7</sup> Underlying this general pattern is a large degree of variation in individual country performance, with growth peaks and valleys across various regional groupings and time periods. However, the overall trend is of an increasing distance between countries in different income brackets, although Pritchett (1997) also shows evidence of convergence at the top of the distribution (that is, among the group of today’s high-income countries).

Once different weights are assigned to countries based on their population (using the international inequality approach), the global income distribution appears to have improved. For example, Bourguignon, Levin, and Rosenblatt (2004) demonstrate a decrease in world income inequality between 1980 and 2002, as long as the relevant inequality measures are not too sensitive to the distance of mean income from the bottom.<sup>8</sup> Using the Gini, the Theil index, and mean logarithmic deviation Atkinson and Brandolini (2004) observed a similar decrease in global income inequality between 1970 and 2000. However, these approaches do not take into account inequality within countries, which has been steadily increasing since the late 1980s (World Bank 2005). Nonetheless, the extent to which increases in inequality within countries have offset the decreases in inequality between them is a hotly debated subject.<sup>9</sup> Therefore the overall direction of change in global inequality since the 1980s is not clear.<sup>10</sup>

---

<sup>7</sup>The ratio of per capita incomes of the richest and poorest country in the sample has grown by a factor of more than five.

<sup>8</sup>Bourguignon, Levin, and Rosenblatt (2004) show that it is possible to produce rising inequality statistics if, for example, the sensitivity of the Atkinson inequality index to deviations from mean income at the bottom of the distribution is set sufficiently high (over five).

<sup>9</sup>Bourguignon and Morrison (2002) argue that inequality between countries has been responsible for most of the time-series variation in global inequality. See also Milanovic (2002), who shows that in 1993, inequality between countries accounted for three-quarters of global inequality.

<sup>10</sup>Some of the studies examining global inequality have relied on parameterized Lorenz curves to add the within-country dimension to the analysis: see for example, Sala-i-Martin (2002a), Sala-i-Martin (2002b), and Bhalla (2002). Others, such as Milanovic (2002) and World Bank (2005), have built up the global distribution from household surveys.

Bourguignon, Levin, and Rosenblatt (2004) offer a “mobility” argument to reconcile the seemingly divergent strands of the literature on intercountry and international inequality. Most of the improvement in global income distribution since the mid-1980s has been driven by increases in the incomes of millions of people in East and South Asia. Thus the individuals at the bottom of the income distribution today are not the same as the poor of 20 years ago. Therefore “those who insist upon equal-weights inequality and corresponding worsening of the distribution have in mind the implicit mobility argument. For them, the fact that some world citizens lost (for example, in Sub-Saharan Africa or the Former Soviet Union) is not necessarily compensated by the fact that others, initially poorer, in China or India have gained. The initial income position matters and the social cost of falling incomes is not compensated by the social gain of increasing incomes, even if these changes take place in the same income range” (Bourguignon, Levin, and Rosenblatt 2004: 21).

\*\*\* Talk about national accounts versus household survey to anchor mean incomes!! The reasons behind the discrepancies are not yet clear: data sources, years covered, etc.

### 3 Methodology: GIDD

The GIDD framework is based on CGE-microsimulation methodologies developed in the recent literature, including Bourguignon, Robillard and Robinson (2003); Chen and Ravallion (2003); and Bussolo, Lay, and van der Mensbrugghe (2005). The starting point is the global income distribution in 2000, assembled using data from household surveys for 84 countries and data on income groups (usually vintiles) for the remaining countries; the final sample covers 91 percent of the world population (see Annex 1 for a full detailed list).<sup>11</sup> The hypothetical 2030 distribution is then obtained by applying three main exogenous changes to the initial distribution: (a) demographic changes, including aging and shifts in the skill composition of the population; (b) shifts in the sectoral composition of employment; and (c) economic growth, including changes in relative wages across skills and sectors.

---

<sup>11</sup>Throughout the paper, when we talk about the global distribution, we are indeed referring to the GIDD’s sample covering 91 percent of the world population.

### 3.1 Conceptual Framework

GIDD’s framework is depicted in Figure 1. Our simulations will include the expected changes in the shares of population by groups formed by age and education characteristics (top boxes of Figure 1). The future changes in population shares by age (upper left part of Figure 1) are taken as exogenous from the population projections provided by the World Bank’s Development Data Group. Therefore, we assume that fertility decisions and mortality rates are determined outside the model. The change in shares of the population by education groups incorporates the expected demographic changes (linking arrow from top left box to top right box in Figure 1). Next, new sets of population shares by age and education subgroups are computed and household sampling weights are re-scaled according to the demographic and educational changes above (larger box in the middle of Figure 1). In a second step, the demographic changes will impact overall labor supply by age and skill groups. These changes are incorporated into the CGE model to simulate overall economic growth, growth in relative incomes by education groups and sector reallocation of labor (link between the middle and bottom rectangles). Finally, the results of the CGE are passed-on to the re-weighted household survey (bottom link in Figure 1).

In reality these changes take place simultaneously, but in the GIDD’s simplified framework they are accommodated in a sequential fashion. In the first step, total population in each country is expanded until it reaches the World Bank’s projections for 2030. The structure of the population is also changed; for example, as fertility rates decrease and life expectancy increases, older age cohorts will become larger in many countries. To accommodate these changes in the survey data, larger weights have been assigned to older people than those assigned to younger individuals. In the next step, workers move from traditional agricultural sectors to more dynamic industrial and service sectors, and new incomes are estimated for these movers. Finally, consistent with an overall growth rate of real income per capita, changes in labor remuneration by skill level and sector are applied to each worker in the sample depending on their education and sector of employment. The number of workers changing sector of occupation and the growth differential in labor remuneration which are used to “shock” the micro-data are consistent with the results of the global computable general equilibrium (CGE) model described in the previous Section. (Note that the outcomes of the CGE model are also influenced by the same demographic changes described above.)

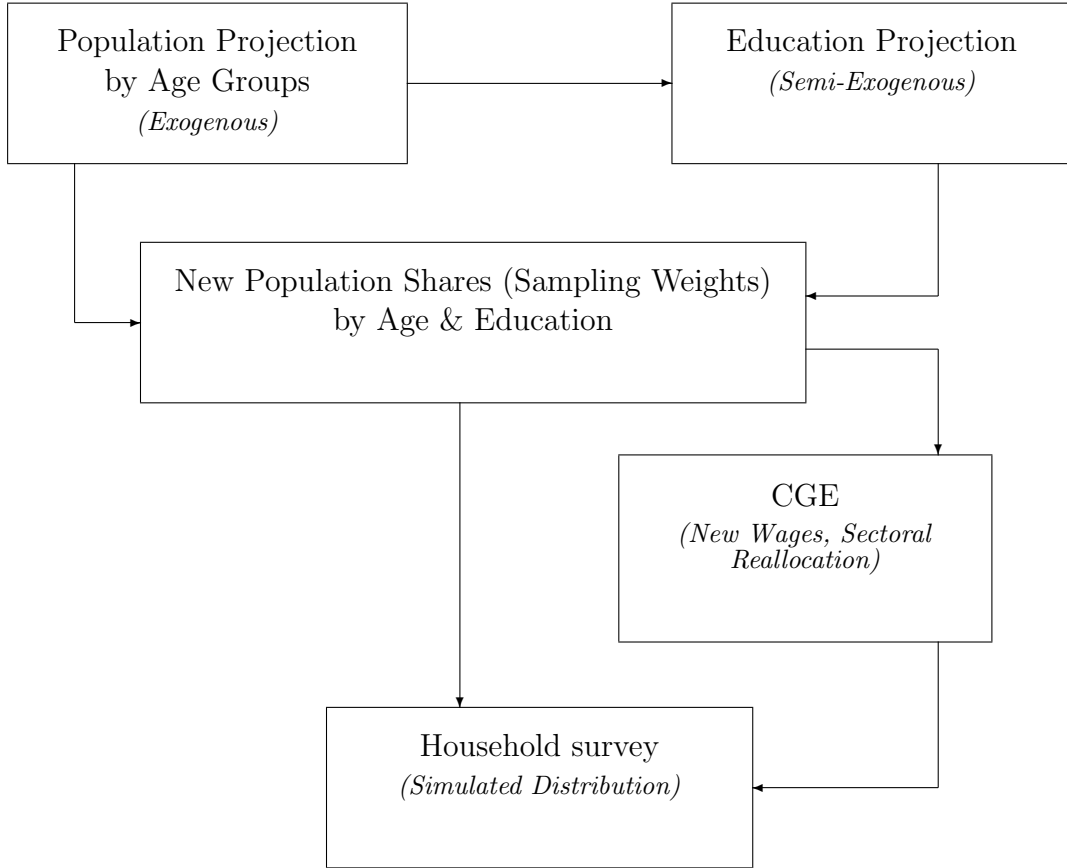


Figure 1: Empirical Framework

The sequential changes described above reshape national income distribution under a set of strong assumptions. In particular, income inequality within population subgroups formed by age, skills, and sector of employment is assumed to be constant over the period. Moreover, data limitations affect estimates of the initial inequality and its evolution. Although consumption expenditure is a more reliable welfare measure than income, and its distribution is normally more equal than the distribution of income, consumption data are not available for all countries' surveys. To get a global picture, the present study had to include countries for which only income data were available. Finally, measurement errors implicit in purchasing power parity exchange rates, which have been used to convert local currency units, also affect comparability across countries. The resulting income distribution should thus not be seen as a forecast of what the future distribution might look like; instead it should be interpreted as the result of an exercise that captures the *ceteris paribus* distributional effect of demographic, sectoral, and economic changes. Although the results of this exercise provide a good starting point for debating potential policy trade-offs, they should not be used as the basis for detailed policy blueprints.

Notice that within the GIDD, the *convergence* component of the global income distribution, i.e. the growth in average incomes, and the *dispersion* component, i.e. the within-country distributional effect, will be determined in a simultaneously consistent way. In other words, if the exogenous changes in a country’s demographic structure is associated with higher growth in per capital incomes but also with higher inequality, these two effects will be captured by our model. The impact of the *convergence* and *dispersion* components of global inequality will be determined by the country’s initial position in the global distribution. Thence, the global distributional effect of higher-than-average growth rates in poor countries (those in the lower part of the global distribution) will have an inequality-reducing effect; the global distributional effect of changes in within-country dispersion will also depend on the country’s initial position in the global distribution. The rest of this section is devoted to the detailed explanation of the empirical methods behind the framework just described. The discussion is separated between socio-demographic changes—including shifts in age groups and education attainments, and economic changes—covering overall household income growth, changes in skilled-to-unskilled wage premiums, and sectoral reallocation (out of agricultural activities).

## 3.2 Socio-Demographic Changes

### 3.2.1 Reweighting Procedure

As it is depicted in the top part of Figure 1, the starting point of our microsimulation exercise is a set of exogenous demographic changes: population size and its structure (in terms of age groups) are modified following the World Bank population projections. The microsimulation model accounts for these changes by adjusting (or re-calibrating) the household survey data by means of a re-weighting procedure following Cai, Creedy, and Kalb (2006).

Define  $\mathbf{w} = (w_1, \dots, w_n)$  as a vector containing the survey design weights for each individual included in the sample such that the total population,  $N$ , can be computed by the following expression:<sup>12</sup>

$$N = \sum_{i=1}^n w_i \tag{1}$$

---

<sup>12</sup>The reliability of equation (1) is subject to a previous process reconciling household survey and national accounts data, for details see Robilliard and Robinson (2003).

By the same token, given a partition rule  $\wp$  (say by age and skill groups), the population in each of the  $m = 1, \dots, M$  subgroups ( $N_m$ ) can be obtained using the expression below:

$$N_m = \sum_{i \in m} w_i \quad (2)$$

Using equations (1) and (2) we can compute the population share for subgroup  $m$ :

$$\nu_m = \frac{N_m}{N} \quad (3)$$

Our reweighting procedure generates a new vector of sampling weights,  $\hat{\mathbf{w}}$ , such that the population share of the  $M$  subgroups are equal to the target values  $\hat{\nu}$ :

$$\hat{\nu}_m = \frac{\hat{N}_m}{\hat{N}} = \frac{\sum_{i \in m} \hat{w}_i}{\sum_{i=1}^n \hat{w}_i} \quad (4)$$

Where  $\hat{N}_m$  and  $\hat{N}$  are the expected population in subgroup  $m$  and the total population, respectively; the information on  $\hat{N}_m$  and  $\hat{N}$  is taken from the population projections by age groups provided by the World Bank's Development Data Group. Additionally, the distance between the new and the original sampling weights,  $D$ , is minimized to attenuate the change in survey design imposed by the reweighting process. Therefore the reweighting procedure minimizes  $D = \sum_{i=1}^n |w_i - \hat{w}_i|$  subject to equation (4); this problem can be summarized by the following Lagrangean:

$$L = \sum_{i=1}^n |w_i - \hat{w}_i| + \lambda \left( \hat{\nu}_m - \frac{\sum_{i \in m} \hat{w}_i}{\sum_{i=1}^n \hat{w}_i} \right) \quad (5)$$

The reweighting procedure modifies the household survey data for it to be consistent with the assumptions made about the ex-ante values of the population aggregates  $\hat{\nu}_m$ . If we were only interested in accommodating ex-ante changes in the population structure, we could use the World Bank population projections by age groups to construct aggregates  $\hat{\nu}_m$  and then use equation (5) to generate the new weights.<sup>13</sup> Nonetheless, our analysis considers the distributional effects of simultaneous changes in two population characteristics: age and education. In the following subsection we explain how

---

<sup>13</sup>Using the Stata commands that accompany this paper, it is possible to undertake a reweighting procedure that accommodates *only* changes in the population structure.

to project educational attainments in a way that there are consistent with the demographic projections. Equation (5) can be use to compute a new set of sampling weights that will achieve the projections on demographic and educational attainments.

### 3.2.2 Projecting Educational Attainments

Given some degree of heterogeneity in educational attainments across age groups, a change in the population structure will affect overall skill endowments. For instance, assume that at time  $t$  young individuals are more educated than older ones, then as time passes, the old and unskilled of today will be substituted by young and more skilled individuals. Therefore at time  $t + 1$ , the overall skill endowments (or the average national educational attainment) increases as a consequence of the change in the structure of the population (even in the absence of policies intended to increase educational attainments).

To take this linkage into account, the population shares by educational groups are extrapolated along with the population projections. As we show in the top part of Figure 1, The World Bank population projections are used as the inputs to extrapolate the shares of population by education groups (thence its classification as a *semi-exogenous* component). Age and skills are both included in our partition rule  $\wp$  therefore, at time  $t$ , the population will be divided into subgroups formed by individuals in different age *and* skill categories. The key assumption behind our educational attainment projections is that the distribution of skills within age groups remain constant over time. For example, if at time  $t$  half of the population in the cohort formed by individuals whose age is between 25 and 30 have post-secondary education, then, after 10 year (at  $t + 1$ ), half of the population between 35 and 40 will have post-secondary education.<sup>14</sup> This mechanical way of extrapolating educational achievements will yield the target (or expected) population shares for subgroups of age *and* skills:  $\widehat{\nu}_m$ . The values in  $\widehat{\nu}_m$  are then substituted into equation (5) to generate the new set of sampling weights  $\widehat{\mathbf{w}}$ .

Several caveats inherent to our reweighting procedure should be mentioned. Throughout the reweighting exercise, within-household structure is not modified. Therefore, to simulate, for example, an ex-ante situation where the share of older and more skilled individuals will be larger (i.e. a typical case of a country reaching the final stages of its

---

<sup>14</sup>In the Stata implementation, educational attainments can also be extrapolated assuming that the educational attainments within age cohorts improve over time.

demographic transition), the reweighting procedure increases the weight of households whose members tend to be older and more educated (relative to household with other characteristics). This approach contrasts with one where individuals (rather household) weights are modified and hence the within-household structure is allowed to change.<sup>15</sup> The second crucial assumption behind our reweighting method is that all personal characteristics within subgroups formed by age and skills remain constant over time. In other words, the old and skilled of tomorrow will have the same characteristics as the old and skilled of today. The consequence of this assumption is that the reweighting process will alter the distribution of all other personal characteristics that are correlated with age and education.

### 3.3 Economic Changes

The demographic changes being modeled will cause a change in overall labor supply and in the supply by education groups. Given a labor demand, these shifts in labor supply will have an impact on wages and the aggregate demand. These general equilibrium changes in relative prices and wages cannot be captured by a microeconomic model, therefore we have to use a Computable General Equilibrium (CGE) model.

**\*\* Perhaps Denis or Maurizio can explain better this part \*\***

#### 3.3.1 Labor Reallocation

The CGE model will predict the number of workers moving out of the traditional agricultural sector into the more modern industrial and service sectors. Workers will chose to abandon the agricultural sector if this choice represents an increase in their income, hence sectoral reallocation of labor will have an impact on income distribution.

To chose who is leaving the agricultural sector we estimate the conditional probability of being a worker in the non-agricultural sector via a probit equation. The probability of observing individual  $j$  working in the non-agricultural sector ( $NA_j = 1$ ) is modeled in the following way:

$$Pr(NA_j = 1) = P(\mathbf{X}_j, \mathbf{Z}_j) \tag{6}$$

---

<sup>15</sup>In the Stata implementations, the user can choose whether to perform the reweighting at the household or at the individual level.

Where  $\mathbf{X}_j$  and  $\mathbf{Z}_j$  are vectors of personal and household characteristics of individual  $j$ , respectively. the workers in the agricultural sector are ordered based on their probability of being in the non-agricultural sectors (equation 6). Workers with higher probabilities to be in non-agricultural sectors are moved out of the agricultural sector up to a point where the predicted shares of workers by sectors is satisfied.

Once the agricultural workers with a higher likelihood of being in non-agricultural sectors have changed sector of employment, the next step is to assign them a labor remuneration. Firstly, we estimate a mincer equation for workers in agricultural ( $A$ ) and non-agricultural ( $NA$ ) sectors:

$$\ln(Y)_{j,s} = \mathbf{X}_{j,s}\boldsymbol{\beta}_s + \varepsilon_{j,s} \quad s = (A, NA) \quad (7)$$

Movers will *carry* with their personal endowments ( $\mathbf{X}_j$ ) and their residual ( $\varepsilon_j$ ). Nevertheless once they *arrive* to the non-agricultural sectors, their vector of personal characteristics  $\mathbf{X}_j$  will be rewarded with *prices*  $\boldsymbol{\beta}_{NA}$  and their residuals will be re-scaled to take into account the differences in the distribution of unobservables between the agricultural and non-agricultural sectors. Hence assuming worker  $j$  is a mover her income assignment function will be defined as:

$$\ln(Y)_{j,NA} = \mathbf{X}_j\boldsymbol{\beta}_{NA} + \varepsilon_j^* \quad (8)$$

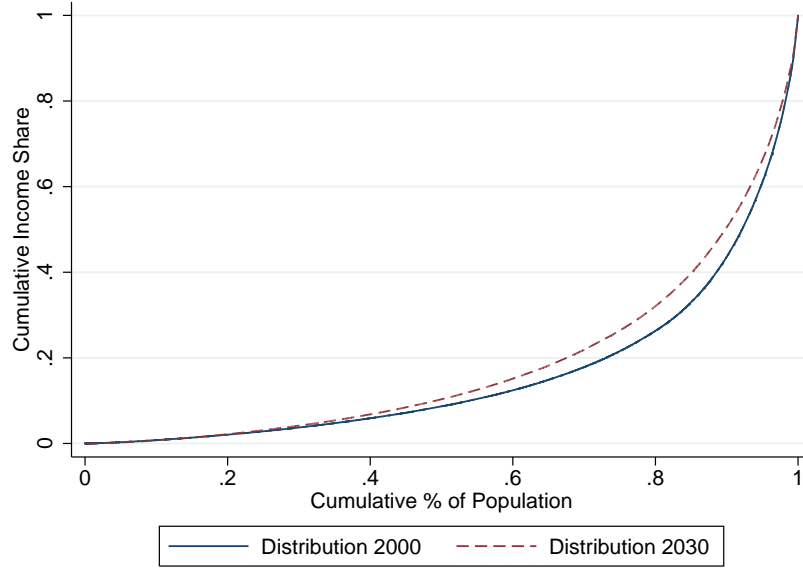
where  $\varepsilon_j^* = \varepsilon_{j,A}(\sigma_{\varepsilon,NA}/\sigma_{\varepsilon,A})$  and  $\sigma_{\varepsilon,s}$  is the standard deviation of the distribution of residuals in sector  $s$ .

### 3.3.2 Economic Growth

## 4 The Global Income Distribution in 2030

We use the methods developed in the previous section to “roll the economy” to 2030. There are plenty of interesting results emanating from this exercise; the prospects for global growth have been discussed in ? and Bussolo et al. (2007a,b). In this study we concentrate in the global distributional effects behind the expected changes in per capita incomes and its distribution within countries.

Figure 2: Lorenz Dominance



In Figure 2 we plot the Lorenz curves for the global income distribution in 2000 and 2030. The distribution in 2030 Lorenz-dominates the distribution in 2000, i.e. global income inequality is better distributed in 2030 as compared with 2000—regardless of the inequality measured being used. This can be easily verified by looking at the inequality statistics reported in Table 1 showing a reduction in inequality for the Gini, the Theil, and the mean logarithmic deviation. The rest of this section analyzes the causes behind this distributional change in terms of the *convergence* and *dispersion* components. We show that the reduction in global income inequality between 2000 and 2030 is the outcome of two opposing forces: the inequality-reducing *convergence* effect and the inequality-enhancing *dispersion* effect (Table 1).

Table 1: Global Income Inequality

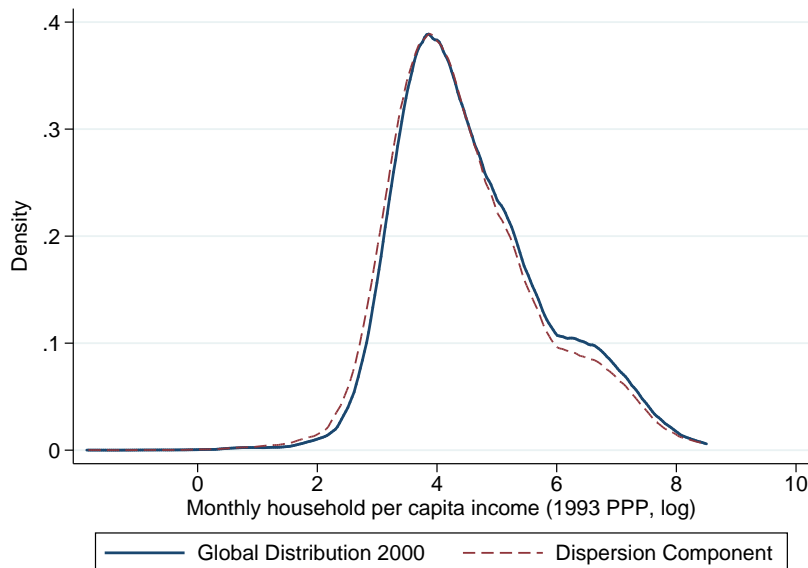
Index	2000	2030	Dispersion	Convergence
			Only	Only
Gini	0.678	0.630	0.682	0.617
Theil	0.926	0.764	0.959	0.720
Mean Log Deviation	0.897	0.774	0.907	0.737

Data source: Authors' own calculations using data from GIDD

## 4.1 Dispersion Component: Intra-Country Inequality at the Rise

Within-countries, income distribution will be altered by: demographic changes, changes in skilled-to-unskilled wage premia, and rural-urban migration. In Figure 3 we plot non-parametric kernel densities of the global income distribution in 2000 together with a hypothetical distribution capturing only the changes in within-country inequality between 2000 and 2030. The hypothetical distribution was created by dividing household incomes in 2030 by the country-specific growth rate on average incomes between 2000 and 2030. In other words, the dispersion component is the outcome of all the changes outlined in Section 3 keeping constant average incomes in each country.

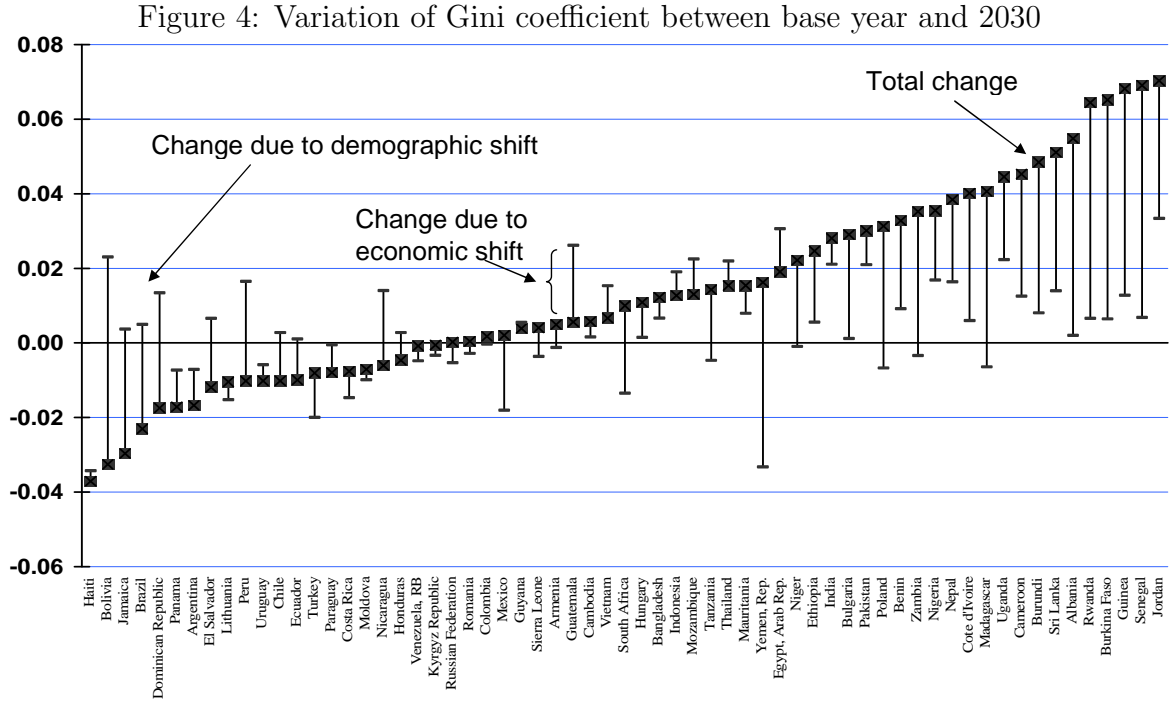
Figure 3: Dispersion Component 2000-2030



Overall, distributional changes within countries has an inequality-enhancing effect, with the global income distribution increasing in half of a Gini point from 67.75 to 68.20 (see Table 1). Within-country income distribution is affected by two sets of factors: shifts in the *demographic structure* of the population, in terms of aging and education attainment, and changes in rewards for *individuals' characteristics*, such as their education level, experience, sector of employment, and so on. Therefore, the changes in income distribution within each country can be further decomposed into changes due to shifts in the demographic structure of the labor force and changes due to adjustments in the rewards to personal characteristics. Creating a hypothetical global income distribution where the only changes occurring between 2000 and 2030 are the shifts in the demo-

graphic structure within each country, we can show that the global Gini coefficient would have remained constant. Hence the *dispersion* component is basically explained by changes in changes in rewards to individual's characteristics.

The rather modest impact brought about by the dispersion component can be hiding important country-specific changes that at the global level end up canceling out each other. To explore this possibility Figure (xxx) shows the change in the Gini coefficient for each country between 2000 and 2030. More than two-thirds of low- and middle-income countries in the study sample, comprising 86 percent of the population in the developing world, are projected to experience a rise in inequality by 2030. For some countries the increase is quite significant (see Figure 4). The pure demographic component is depicted by the horizontal bars in Figure 4. Notice that there is very little correlation between the distributional effects of demographic changes and the total change in within-country inequality. Therefore, the general positive shifts in country-specific Gini coefficients can be attributable to increases in the skilled-to-unskilled wage premium (the difference between solid squares and the horizontal bar in Figure 4).



Almost all the countries expecting a reduction in inequality are highly unequal Latin American economies. On the other hand, inequality-reducing changes take place in African and Asian countries with relatively low initial inequality. As we mentioned it before, widening gaps in factor rewards, and particularly in the premium paid for higher skills, tend to produce larger changes in inequality and generally determine

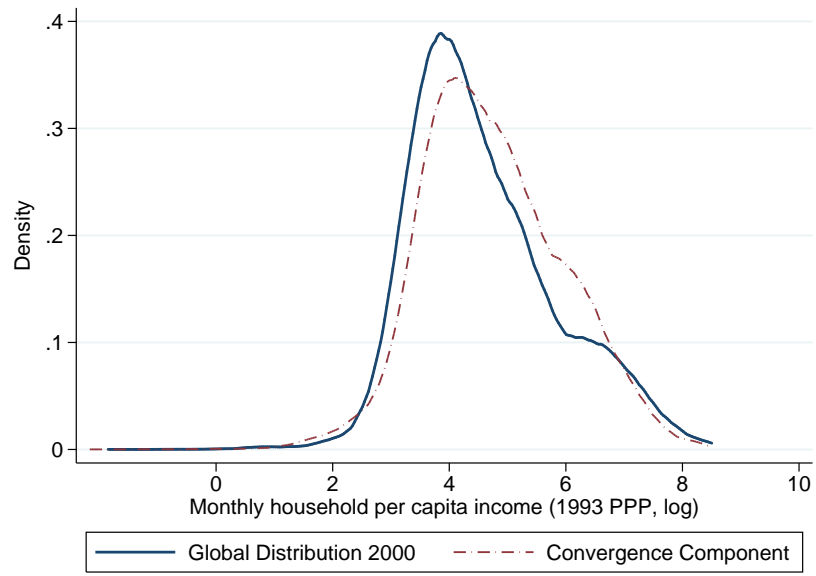
the overall direction of the effect. The results therefore illustrate a “convergence” of income distributions across countries, which can be interpreted as a manifestation of the Kuznets hypothesis or as a consequence of the globalization-induced equalization of factor prices.

## **4.2 Convergence Component: The Poor World is Catching-Up**

There are three aspects determining the existence, sign, and magnitude of each country’s contribution to the convergence component: (1) a particular country will have a global distributional impact if its rate of growth differs from the global average; (2) given that condition (1) is satisfied, the sign of the distributional effect will depend on the country’s initial position in the global distribution; and (3) the magnitude of the impact is determined by the size of the growth rate differentials (with respect the global average) and the country’s share in the global population. Hence, initial poor countries with higher-than-average growth rates will have a inequality-reducing effect with its magnitude being determined by the size of the country’s population.

In Figure 5 we show the change in the global income distribution that is due to differences in growth rates between countries keeping global average income constant. Had the convergence effect been the only change taking place between 2000 and 2030, global inequality would have reduced in more than 6 Gini points (see Table 1). Therefore the documented improvement in the global distribution is entirely explained by growth rates differentials across countries with poor countries catching up with middle- and high-income countries.

Figure 5: Convergence Component 2000-2030



## 5 Conclusions and Future Research

## References

- BOURGUIGNON, F., V. LEVIN, AND D. ROSENBLATT (2004): “Declining International Inequality and Economic Divergence: Reviewing the Evidence Through Different Lenses,” *Economie Internationale*, (4Q), 13–26.
- BOURGUIGNON, F., AND C. MORRISSON (2002): “Inequality among World Citizens: 1820-1992,” *American Economic Review*, 92(4), 727–744.
- CAI, L., J. CREEDY, AND G. KALB (2006): “Accounting For Population Ageing In Tax Microsimulation Modelling By Survey Reweighting,” *Australian Economic Papers*, 45(1), 18–37.
- MILANOVIC, B. (2002): “True World Income Distribution, 1988 and 1993: First Calculation Based on Household Surveys Alone,” *Economic Journal*, 112(476), 51–92.
- (2005): *Worlds Apart: Measuring International and Global Inequality*. Princeton University Press, Princeton and Oxford.
- (2006): “Global income inequality : what it is and why it matters,” Policy research working paper series, The World Bank.
- QUAH, D. T. (1996): “Twin Peaks: Growth and Convergence in Models of Distribution Dynamics,” *Economic Journal*, 106(437), 1045–55.
- ROBILLIARD, A. S., AND S. ROBINSON (2003): “Reconciling Household Surveys and National Accounts Data Using a Cross Entropy Estimation Method,” *Review of Income and Wealth*, 49(3), 395–406.
- SALA-I MARTIN, X. (2006): “The World Distribution of Income: Falling Poverty and ... Convergence, Period,” *The Quarterly Journal of Economics*, 121(2), 351–397.
- WORLDBANK (2005): *World Development Report 2006: Equity and Development*. Oxford University Press for the World Bank, Oxford and New York.
- (2006): *Global Economic Prospects 2007: Managing the Next Wave of Globalization*. Oxford University Press for the World Bank, Oxford and New York.