Policy Options for Meeting the Millennium Development Goals in Brazil: Can micro-simulations help?[1]

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Abstract: This paper investigates whether micro-simulation techniques can shed any light on the types of policies that should be adopted by countries wishing to meet their Millennium Development Goals. We compare two families of micro-simulations. The first simply decomposes required poverty changes into a change in the mean and a reduction in inequality. The second is based on a richer model of behavior in the labor markets. Although the former usefully highlights the importance of inequality reduction, it appears to be too general to be of much use for thinking about policies. The second family of micro-simulations points to the importance of combining different policy options, such as educational expansions and targeted conditional redistribution schemes, in order to ensure that the poorest people in society are successfully reached. But the absence of market equilibria in these statistical models, as well as the strong stability assumptions which are implicit in their use, argue for extreme caution in their interpretation.

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1. Introduction

In September 2000, the member states of the United Nations unanimously adopted a document known as the Millennium Declaration. After consultations with a number of international organizations within the UN system, as well as the IMF, the World Bank and the OECD, the General Assembly recognized the Millennium Development Goals (MDG) as integral components of the implementation of that Declaration. There are eight such goals, each corresponding to a key development aim in one dimension of human welfare. They are listed in Table 1. Associated with the eight goals, there are eighteen specific targets, which quantify the broad goals in a measurable manner. Finally, there are forty-eight indicators in total, each of them associated with a specific target. These are meant to be monitoring variables, through the evolution of which progress towards the goals can be evaluated. For a complete listing of goals, targets and indicators, see: www.worldbank.org/mdg.

Table 1. The Millennium Development Goals

Goal	**Title**
1	Eradicate Extreme Poverty and Hunger
2	Achieve Universal Primary Education
3	Promote Gender Equality and Empower Women
4	Reduce Child Mortality
5	Improve Maternal Health
6	Combat HIV/AIDS, malaria and other diseases
7	Ensure Environmental Sustainability
8	Develop a Global Partnership for Development

These goals and their associated collection of targets and indicators have already succeeded, to a large extent, in at least one of their objectives, namely raising awareness of the issues which they seek to address and focusing the mind of policy-makers – national and international – on the need to secure measurable progress along various dimensions of human welfare in a relatively short period of time: most targets specify objectives which should be accomplished no later than 2015. As part of the effort, some of the multilateral institutions have started monitoring programs, which compile and present up-to-date information on how different countries and regions are doing with respect to each target.

Based on the results of these periodic monitoring exercises, questions have begun to be asked in a number of countries as to whether this or that goal can in fact feasibly be reached by 2015. In some nations, debates about policies to help meet some of the goals have entered the political arena. Internationally, at least two UN agencies have teamed up to simulate progress and requirements for countries to meet their First MDG Target, namely to halve the incidence of extreme poverty which prevailed in 1990, by 2015.[3]

The purpose of this paper is to investigate whether modern micro-simulation techniques can shed any light on some of the policy options available to countries which want to meet some of their Millennium Development Goals. Throughout the article, we argue for considerable circumspection: all of the simulations we present are essentially statistical exercises. Although they differ in the extent to which agent behavior is taken into account, none of them is based on models where prices are endogenously determined, and thus none takes full account of market adjustments towards equilibrium, or of subsequent agent responses.

Nevertheless we argue that, subject to the necessary caution and humility, some valuable lessons can indeed be learned from micro-simulation-based social forecasting. We apply our analysis to a single country – Brazil – and to three of the eight goals. Table 2 lists the five indicators which we include in this exercise. The numbers associated to them in the Table are their official numbers in the Millennium Development Goals.

Table 2. Specific MDG Indicators Considered in This Paper

Goal 1: Poverty and Hunger	1. Proportion of the population below $1 per day 2. Poverty gap ratio
Goal 2: Primary Education	6. Net enrollment in primary education
Goal 3: Gender Equality	9. Ratio of girls to boys in primary, secondary and tertiary education. 11. Ratio of women to men in wage employment in the non-agricultural sector.

[3] This was a simulation exercise for Latin America, undertaken jointly by the UNDP and ECLAC, alongside Brazil's IPEA. See ECLAC and UNDP, forthcoming, for a full report.

The paper is organized as follows. In the next section we present a simple "growth and inequality" simulation, which yields all combinations of growth rates and "Lorenz-convex" inequality reductions which are statistically consistent with achieving the MDG Target 1: "Halving, between 1990 and 2015, the proportion of people whose income is less than one dollar a day". We then argue that, while some useful insights can be derived from this exercise, implications for policy are necessarily limited by the behavioral paucity of the underlying analysis. Accordingly we turn, in Section 3, to an approach which is structurally richer, by virtue of taking into account observed patterns of behavior with respect to key agent decisions, such as educational attainment, occupational choice and earnings. We find that this approach generates more detailed and specific counterfactuals, which may be useful in guiding policy interventions. We warn, however, that both the absence of endogenous price responses in the model and the strength of the assumptions of behavioral stability which are maintained, imply that the simulation results should not be understood as predictions.

2. Growth and Inequality: a Statistical Perspective [4]

The first target associated with Millennium Development Goal number One is that countries should halve, between 1990 and 2015, the proportion of their population living in households with per capita expenditure or income levels equal to or less than one dollar per day, measured in purchasing power parity terms. Since this is a poverty reduction target, it makes sense to start thinking about it in terms of the two basic manners in which the extent of poverty in any given distribution can be reduced: growth in the mean and/or reduction in inequality.

A measure of poverty ? in a given income distribution F(y) is always defined with respect to a poverty line z, which separates the poor from the non-poor. It is therefore always the case that poverty is a functional of the distribution of income and of the poverty threshold: ? = ? (F(y), z). As we just saw, the Millennium Poverty Reduction

[4] This section draws heavily on ECLAC and UNDP, forthcoming. The methodology presented here was developed originally for the preparation of that Report. Both authors were fortunate to work on the team that prepared it, and are grateful to all other team members – especially Ricardo Paes de Barros – for their guidance.

Target was formulated in terms of the poverty incidence indicator P_0, so that this functional is simply $P_0 = F(z)$.[5]

In order to consider how economic growth and changes in inequality contribute to changes in the incidence of poverty, P_0, it is convenient to draw on the established result[6] that:

$$L'(p) = \frac{F^{-1}(p)}{m_y}$$

where L'(p) denotes the first derivative of the Lorenz Curve:

$$L(p) = \frac{1}{m_y} \int_0^{y(p)} x f(x) dx = \frac{1}{m_y} \int_0^{p} F^{-1}(p) dp$$

associated with the income distribution p = F(y). It immediately follows that:

$$L'(P_0) = \frac{F^{-1}(P_0)}{m_y} = \frac{z}{m_y}$$

Thus:

$$P_0 = L'^{-1}\left(z/m_y\right)$$

This merely states that the incidence of poverty is completely determined by the poverty line, the mean of the distribution, and its Lorenz Curve.[7]

This is useful for our investigation of reductions in extreme poverty, since we can simulate the effects of economic growth as changes in mean income (μ_y) and the effects of inequality as changes in the Lorenz Curve, L(p), which is independent of the mean by construction. In particular, for any poverty incidence rate $P^* < P_0(F(y), z)$, there should

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[5] On the definition and properties of the P_α family, see Foster, Greer and Thorbecke (1984).
[6] See, e.g., Kakwani (1980) and Deaton (1997).
[7] This fact has long been known, and indeed long been used to decompose observed changes in poverty into components due to ‘growth’ and ‘inequality’. There is no single ‘right’ decomposition, and at least three approaches have been proposed, namely those due to Datt and Ravallion (1992), Kakwani (1993) and Tsui (1996). See Ravallion (2000) for a survey. While the basic approach used in this Section falls squarely in that tradition, it differs in at least one respect: since we are concerned with simulating the future – a form of extrapolating out of sample – we construct and analyse *sets* of arbitrarily defined counterfactual distributions, rather than focusing on decomposing poverty changes between well-defined specific actual distributions.

exist (a number of) hypothetical distributions F*, with mean level μ_y* and Lorenz curve L*(p), which would have a poverty incidence of $P^* = L^{*'-1}\left(z/m_y *\right)$.

In particular, consider a counterfactual income distribution F*(y*), where:

(1) $$y^* = (1+ß)[(1-a)y + a\mu_y], \quad \text{with } 0 < a < 1,\ ß > 0.$$

This transformation corresponds to a distribution-neutral increase of ß% in everyone's income level, coupled with a redistribution policy consisting of taxing 100a% of everyone's income, and then distributing the revenues equally across every person in the population.

It is easy to see that the mean of the resulting counterfactual distribution would be ß% higher than in the original distribution:

(2) $$\mu_y^* = (1+ß)\mu_y.$$

It is also true that the Lorenz curve of the new distribution would be thus transformed:

(3) $$L^*(p) = (1-a)L(p) + ap$$

And, consequently, that the Gini coefficient of the counterfactual distribution would be a% lower than that for the original distribution[8]:

(4) $$G^*(y) = (1-a)G(y).$$

Given these properties, we refer to the two-parameter (α, β) class of transformations of an income distribution, which is given by (1), as Lorenz-convex transformations.[9] This is clearly a restrictive set of transformations, but it is analytically convenient. For this reason, they have been used before in the literature. They underlie, for instance, the Kakwani (1993) decompositions.

The values of a and ß can be chosen so that equations (2) and (3) hold exactly, satisfying $P^* = L^{*'-1}(z/\mu_y^*)$. The target poverty incidence rate P* can then be written as a functional of the original income distribution, of the relevant poverty line, and of the simulation parameters a and ß:

(5) $$P^* = P_0(a, ß, F(y), z)$$

[8] See the Appendix for a proof.
[9] Analogously, we call any process that leads from L(p) to L*(p), defined as in (3), for 0 < a < 1, a "Lorenz-convex inequality reduction".

Since a and ß can be chosen independently, there is in fact one degree of freedom in the choice of simulation parameters. In other words, given an arbitrary value of either a or ß (subject to $0 < a < 1$, $ß > 0$), there will exist a (positive or negative) value of the other parameter such that (5) holds. One can thus define an isopoverty set for the distribution F(y), for each target poverty incidence P*, with respect to poverty line z, as the set of a, ß pairs that would lead from F(y) to another distribution with poverty rate P*. Formally:

(6) $$I(P^*, F(y), z) = \{(a, ß) \mid P_0(a, ß, F(y), z) = P^*\}$$

When plotted on a, ß space, we will refer to it as the P* isopoverty curve. In the specific case of the MDG poverty reduction target, P* is simply one half of the poverty incidence rate P_0 which prevailed in the country in 1990. In this case, any combination of a rate of inequality reduction (a) and a rate of economic growth (ß) which belongs to I will halve the 1990 incidence of poverty with respect to the extreme poverty line z.

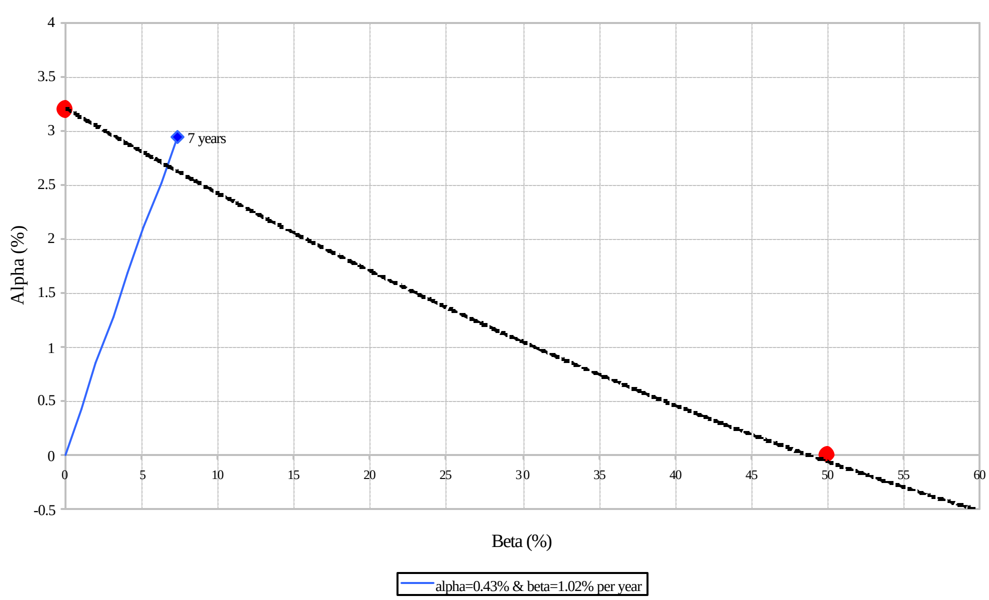
Figure 1 below plots the isopoverty curve for the Brazilian Millennium Development Goal poverty target, which is defined on the basis of the poverty incidence estimated from the 1990 national household survey *Pesquisa Nacional por Amostra de Domicílios* (PNAD).[10] Using a purchasing power parity exchange rate and a thirty-days month, the international U$1/day poverty line was converted to Brazilian Reais at R$22.11 per person per month, in 1999 prices.[11] The proportion of the Brazilian population living in households with total per capita income levels below that line in 1990 was 7.46%. This implies that the MDG poverty reduction target for Brazil would be to reach an extreme poverty incidence of 3.73% by 2015.

[10] The PNAD is Brazil's main nationally representative household survey. It is fielded annually, except in Census years (such as 1991), and covers the entire country, except the rural areas of the states of Acre, Amapa, Amazonas, Para, Rondonia and Roraima. Its sample size in 1990 (1999) was 72,084 (91,546) households. Although there is no better data set for either 1990 or 1999 in Brazil, see Ferreira, Lanjouw and Neri (forthcoming) for a discussion of its shortcomings in measuring incomes, particularly in rural areas.

[11] The international "one-dollar per person per day" poverty line, which originated from the World Bank Research Department, was originally used in 1990 and was expressed in 1985 prices. The World Bank later updated it to U$1.08/day, in 1993 prices. To obtain the monthly poverty line in 1999 Brazilian Reais, we computed z = U$1.08 * 30 * (1/$PPP_{93}$) * Brazil's CPI (September 1999, with base September 1993) = 32.4 * 56.1243 * 38.30 = 22.11. The reader is warned that two of these numbers are measured with considerable error: PPP exchange rates – which aim to calculate cost-of-living adjusted exchange rates across countries - are based on a necessarily incomplete survey of product and service prices. Additionally, Brazilian inflation rates were very high in 1993, so that the choice of base month in that year (i.e. the precise point in time for which the PPP exchange rates were valid) matters considerably for the final 1999 poverty line. Our choice of September 1999 (the PNAD reference month) implies a lower poverty line than using an average CPI for 1993 (as reflected in the World Bank's World Development Indicators (2002) figure for 1998).

Figure 1 plots the combination of cumulative rates of growth in mean per capita incomes from 1990 to 2015 (ß, on the horizontal axis) and the cumulative rates of Lorenz-convex inequality reduction (a, on the vertical axis) which would achieve that target. Table 3 isolates three specific points, for analysis. The first of these is the vertical intercept of the isopoverty curve. It tells us that one way to halve the poverty incidence prevailing in 1990 would be to rely exclusively on inequality reduction: with zero growth in mean incomes, the poverty reduction target would be reached with a 3.4% cumulative decline in the Gini coefficient (through a Lorenz-convex shift of the Lorenz curve).This would imply a fall in the Gini coefficient from 0.61 to 0.59. Alternatively, the same poverty incidence (3.71%) could be reached with no movement in the Lorenz curve, through an accumulated per capita growth rate of 50% - corresponding to an average annual rate of 1.64% over the 25-year period - at the horizontal intercept of the curve.

Figure 1: Brazil's MDG Isopoverty Curve



In between these "pure strategies", there lies a continuum of combinations of inequality reductions and accumulated rates of economic growth which would be consistent with halving Brazil's 1990 poverty incidence. One such point, which might be of interest, is the one arising from the historical performance of the country between 1990 and 1999. Over these nine years, Brazil's mean income in the PNAD grew at an average annual rate of 1.02%, and the Gini coefficient fell at an average annual rate of 0.43%. As the last row in Table 3 indicates, *had this decline in the Gini been attained through a Lorenz-convex inequality reduction*, this pattern would have led to a halving of the incidence of poverty in just under seven years. With a cumulative growth in mean income of 7.35% and a Lorenz-convex fall in inequality of 2.94% (which corresponds to less than two points of the Gini), the Brazilian extreme poverty headcount would have fallen to 3.38%, by 1997.

Table 3: Three points on Brazil's MDG Isopoverty Curve

	Growth (b%)	**Inequality Reduction (a%)**	m	**Headcount**	**Gini**
1990			**232.66**	**7.46%**	**0.6119**
1999	9.56	3.74	**254.90**	**5.29%**	**0.5889**
2015*	0	3.40	232.66	3.71%	0.5911
	50	0.00	348.99	3.71%	0.6119
Historical per year (b=1.02%; a=0.43%):					
1997*	7.35	2.94	249.77	3.38%	0.5939

Source: PNAD/IBGE 1990, PNAD/IBGE 1999 and author's calculation

Notes: z = R$22.11 per person per month, in 1999 values, which corresponds to U$1/person/day.

*Denotes simulated distributions.

Yet, the actual observed incidence of extreme poverty in 1999 was 5.29%, despite the fact that accumulated growth in the PNAD mean income since 1990 was actually 9.56%, and that the 1999 Gini coefficient was 3.74% smaller than in 1990. How can this be? It is simply an indication that the reduction in the Gini coefficient was *not* the result of a Lorenz-convex inequality reduction. The shift of the Lorenz curve between 1990 and 1999 was not a perfect convex combination between the 1990 Lorenz curve and the line of perfect equality, as implied by (3). This can be clearly seen in Figure 2, which was truncated at the median in order to facilitate visualization of the lower tail. In this picture, the lowest (thick) Lorenz curve is that for 1990. The solid thin line is the simulated Lorenz curve corresponding to a convex transformation such as equation (3), with a = 0.0294. The dotted curve is the actual 1999 Lorenz curve. It can be seen that the factual reduction in inequality was not as beneficial to the bottom of the distribution as a Lorenz-convex transformation would have been.

Figure 2: Truncated Lorenz Curves for Brazil; actual and simulated

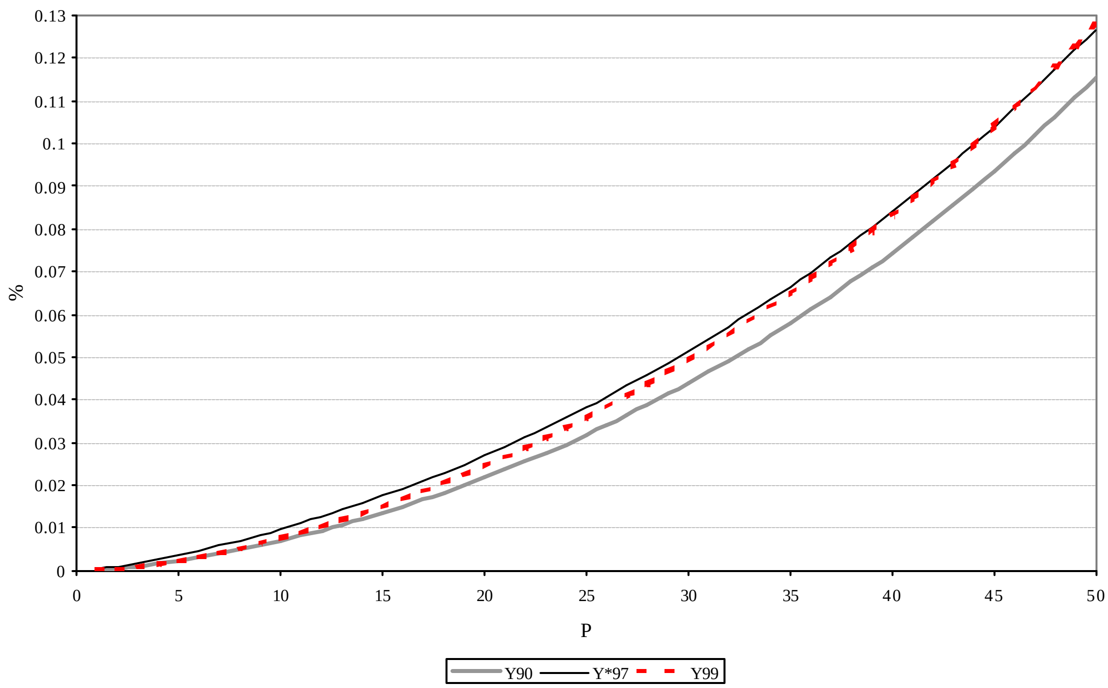
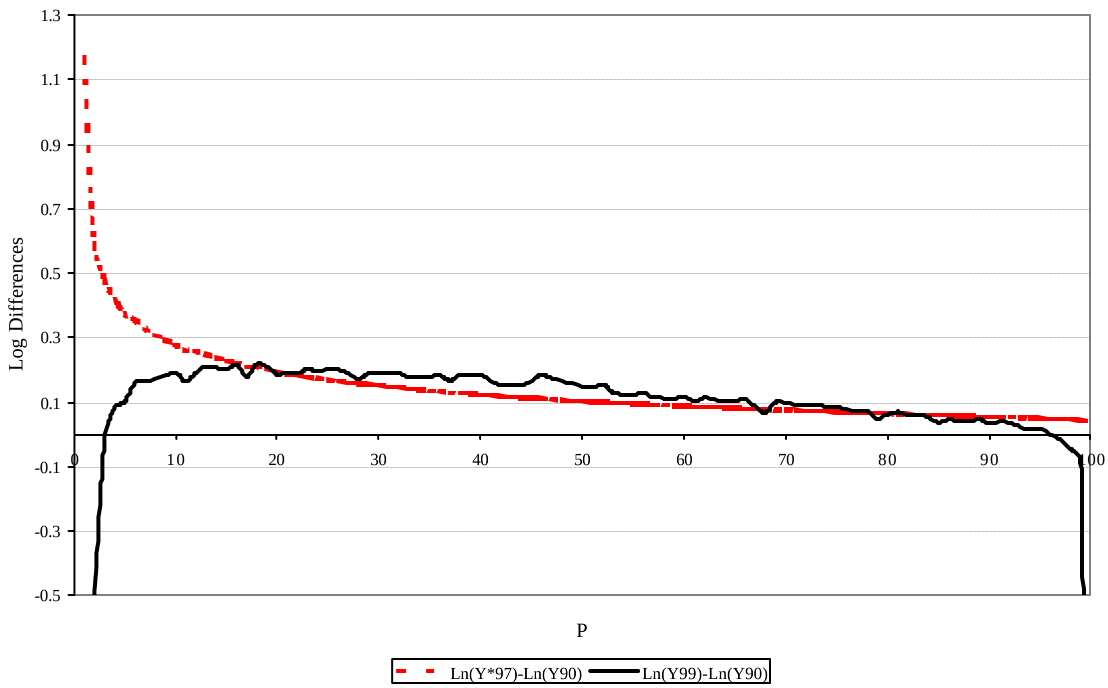


Figure 3: Log Income Differences per Percentile, 1990-1999; actual and simulated



This can be seen even more clearly a few levels of integration below the Lorenz curve. Figure 3 plots the differences in the logarithms of income for each percentile, between two pairs of distributions. The dotted line refers to the difference between the simulated distribution F*(α=0.0294, β=0.0735) and the actual 1990 distribution, whereas the solid line refers to the difference between the actual 1999 and the actual 1990 distributions. Although both distributions have lower Gini coefficients than the 1990 distribution, it is apparent that those distributions are obtained from the 1990 one through rather different processes. In particular, it is clear that the actual changes at the bottom of the distribution were very different from the simple arithmetic simulation implied by equation (3): instead of the large proportional gains predicted by (1), the bottom three or four percentiles suffered considerable losses.

These differences should not come entirely as a surprise. The simulation of a counterfactual income distribution through the application of equation (1) is a simple arithmetic procedure. There is no guarantee whatsoever that it would be consistent either (a) with household behavior in various realms, such as fertility or occupational decisions, which can affect the distribution of income; or (b) a general equilibrium of the markets in the economy.

The exercise described in this section does serve one useful illustrative purpose. It establishes that – at least for a country as unequal as Brazil – inequality reduction could *in principle* be a very effective path towards the eradication of extreme poverty and the meeting of the poverty reduction MDG. A simple two-point reduction in the Gini coefficient (from 0.61 to 0.59) over the entire twenty-five year period *could* achieve the goal, even without any economic growth. Conversely, the accumulated rate of economic growth needed to meet the target at constant inequality is 50%. While the average annual growth rate implied by this number (1.64%) is not high, it nevertheless lies above the rate observed historically in the 1990s. In other words, the inclination of a country's isopoverty curve can provide some guidance as to the statistical trade-off between the growth and inequality reduction rates required to reduce poverty.[12]

[12] Note that this refers only to the statistical trade-off between growth and inequality. Economically, it is quite possible that there be additional trade-offs or, conversely, that some inequality reduction might facilitate growth.

Undertaking a similar exercise for eighteen countries in Latin America and the Caribbean, ECLAC and UNDP (forthcoming) find that only seven countries[13] in the sample would meet their MDG poverty targets if their growth and inequality trends during the 1990s were replicated in 2000-2015. Another six countries would miss the target by 2015, but would thereafter eventually halve the incidence of extreme poverty on the basis of their performance in the 1990s.[14] Finally, a hard core of five countries where either negative economic growth rates or increasing inequality in the 1990s, or a combination of both, implied rising extreme poverty during that decade, would of course never meet the MDG target under the assumption that their performances in the 1990s would extend indefinitely into the future.[15] Turning to consider alternative scenarios, the report found that isopoverty curves in the region were almost universally "flat", implying that the poverty-reduction impact of a percentage-point reduction in the Gini coefficient (under the maintained Lorenz-convexity assumption) was equivalent to that of many percentage points in accumulated economic growth.

The very fact that the poverty-reduction impact of economic growth is relatively weak in Latin America is itself associated with the region's high level of inequality (see, for instance, Bourguignon, 2002). The international evidence strongly suggests that, with everything else constant, inequality reduces the growth elasticity of poverty reduction, so that an additional percentage point in the growth rate has a lower effect on (most) poverty measures in a high-inequality country, than in a more egalitarian one. See Ravallion (1997). Since Latin America is a highly unequal region (and Brazil a highly unequal country), economic growth there translates into lower rates of poverty reduction than elsewhere. This has an important additional implication: going beyond the statistical decomposition reported here, it is likely that reducing inequality will not only reduce poverty directly now, but also that it will augment the future effects of economic growth on poverty.

The general implication is that policies aimed directly at reducing inequality may have high returns in terms of poverty reduction both now and in the future, provided they

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[13] Argentina (pre-crisis), Chile, Colombia, the Dominican Republic, Honduras, Panama and Uruguay.

[14] Brazil, Costa Rica, El Salvador, Guatemala, Mexico and Nicaragua. The Brazilian result differs from ours because those authors assumed a constant inequality rate during the 1990s.

[15] Bolivia, Ecuador, Paraguay, Peru and Venezuela.

do not have high efficiency costs. In the particular case of Brazil, Table 3 revealed that the growth rate required to halve extreme poverty from its 1990 level without any inequality reduction would be 60% higher than the rate actually observed in the 1990s. It also indicated that, in the absence of any economic growth, blanket untargeted redistribution would require a substantial additional fiscal effort (of some 3.4% of GDP). The clear implication is that whichever growth rate can be achieved in the next twelve years should be complemented by redistribution policies which are more directly targeted to the poor. In this way, they can contribute more to poverty reduction, at a lower fiscal cost.

The simple simulation exercise reported in this Section can not take us much further than this. While it was useful in deriving these general conclusions, the exercise has clear limitations. The Brazilian 1990-1999 experience, as illustrated by Figures 2 and 3, provides a good example of how flawed the assumption of Lorenz-convexity can be in approximating real distribution dynamics. The changes in a distribution of household incomes are the complex outcome of a number of underlying economic and social phenomena, such as changes in the productive endowments available to workers in the economy; changes in returns to worker characteristics; changes in participation decisions; changes in family composition; and so on. In the next section, we turn to an empirical model of household income determination which seeks to incorporate some of these key dimensions, in the hope that it can provide more specific policy guidance.

3. Behind the Mean and the Lorenz Curve: can a little microeconomics help?

One reason why a simple transformation of the Lorenz Curve such as that implied by equation (1) can perform poorly in approximating actual observed changes is that household incomes are not random numbers drawn from some statistical law defined over the population. Rather, they are determined by the combination of labor and other incomes accruing to various household members, and thus depend on their individual occupational decisions, on the human and physical assets they own, and on the rates at which the markets remunerate those assets. A simple descriptive model of household income determination might therefore be given by the following four blocks[16]:

Block I: Household Income Aggregation

(7) $$y_h = \frac{1}{n_h}\left[\sum_{i=1}^{n_h}\sum_{j=1}^{J} I_{hi}^{j} y_{hi}^{j} + y_0\right]$$

This identity simply defines a household's income per capita from the sum of labor incomes across occupations (indexed by j) and across household members (indexed by i). y_0 denotes all non-labor incomes accruing to the household, and n_h is household size. I_i^j is an indicator variable that takes the value one if household member i participates in occupation j, and zero otherwise.

Block II: Earnings Equations

(8) $$Log\ y_{hi}^{j} = X_i \beta^{j} + \varepsilon_i$$

Equation (8) is a standard Mincerian earnings equation. In what follows, four such equations are estimated separately. One is for age group 10-15, which is used only in the simulation of a specific policy (*Bolsa Escola*) such as it exists now. Another one is for the age group 10 -18. Two are estimated for those aged 19 and older: one for own-account workers ("conta-próprias") and employers; and another for wage-earning employees.[17] In all cases, workers were assigned to the sectors of their principal occupation. The vector *X*, as is customary, contained characteristics both of the worker and of the job. In this case, *X* included years of schooling (year dummies), age, age squared, age interacted with schooling, a gender dummy, race (white, non-white), formality status, and spatial variables (region of the country, urban/rural). The exact specification and results for the 19-and-older group (for the under-18 group) are reported in Table A1 (Table A2) in the Appendix.

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[16] This model is adapted from Bourguignon, Ferreira and Lustig (1998). Unlike those authors, we do not model fertility decisions, since simulations of that aspect of behavior would be difficult in this particular application. Note, however, that the effects of education which operate through the conditional distribution of family sizes can be substantial. See also Ferreira and Leite (2002).

[17] Dummies are included to distinguish between "com carteira", "sem carteira" and public servants.

Block III: Occupational Structure

(9) $$P_i^s = \frac{e^{Z_i g_s}}{e^{Z_i g_s} + \sum_{j \neq s} e^{Z_i g_j}}$$ where s, j := oc. categories. For those aged 19 or older.

(10) $$P_i^k = \frac{e^{(Z_i . g_k + Y_{-i} a_k + w_i . b_k)}}{\sum_j e^{(Z_i . g_j + Y_{-i} a_j + w_i . b_j)}}$$ For those aged 10-18.

This block models the structure of occupations in the labor force by means of two similar discrete choice models — specifically, two multinomial logits — which estimate the probability of choice of each occupation as a function of a set of family and personal characteristics. Table A3 contains the specification and results for those aged 19 or older, with inactivity and unemployment as the base category. The other occupational categories are self-employment ("conta-própria'); formal private sector employment ("com carteira"); informal private sector employment ("sem carteira"); public service; and being an employer. Table A4 presents the specification and results for those aged 10-18, for whom the choice of occupations is modeled differently: a young person may not attend school (base category), attend school only and not work in the market; or both attend school and work in the market.[18]

Note that the occupational choice model for adults is written in reduced form, since it does not include the wage rate (or earnings) of the individual (or of its family members) as explanatory variables. Instead, his or her productive characteristics (and the averages for the household) are included to proxy for earning potential. This approach is adopted to maintain the econometrics of joint estimation (with Block II) tractable. The model for 10-18 year-olds, on the other hand, is estimated as a structural model, with the predicted earnings from the earnings equation reported in Table A2 included as w_i in the

[18] We do not place any emphasis on the possible interpretations of equations (9)-(10) as reduced forms of utility-maximizing behavioral models. Instead, we interpret them as parametric approximations to the relevant conditional distributions; that is to say, as descriptions of the statistical associations present in the data, under some maintained assumptions about the functional forms of the relevant joint multivariate distributions. See Bourguignon, Ferreira and Leite (2002a) for a more detailed statistical discussion of this kind of counterfactual analysis.

RHS for all youngsters, as a measure of potential earnings.[19] Other incomes accruing to the family – but not to the child – are also included, and denoted by Y_{-i}.

Block IV: The Distribution of Education

(11) $$OPM(e \mid a,r,g,s): P(e_i|M) = \Phi[c(e_i) - Md] - \Phi[c(e_{i-1}) - Md]$$

This block models an individual's choice of final educational attainment (in terms of years of schooling), as a function of his or her age (a), race (r), gender (g) and spatial characteristics (s), which are grouped in the matrix M. Unlike the choices underlying the occupational structure of the population, educational choices follow a specific ordering by years, and are therefore more appropriately represented by an ordered probit model (OPM). This approach models the probability (conditional on M) that an individual chooses education level e_i as the difference between the cumulative normal distribution (F) evaluated at cut-off points estimated for levels e_i and e_{i-1}. The estimation results for (11), containing both the estimated values for d and the seventeen estimated cut-off points, are given in Table A5.

Although it consists only of four basic equations, this model does seem rather more complicated than the one presented in Section 2. There had better be a real gain in understanding and insight, to compensate for the additional complexity. We argue that this gain is real, and arises from the ability to simulate policy outcomes, which were impossible to specify in the more general framework of the previous section. To illustrate this point, we will use equations (7)-(11) to simulate the effects of three different "policies" on the Brazilian distribution of household incomes. Since the purpose of the

[19] The occupational choice model for this age group had to be structural because of the nature of the policy intervention under study for these individuals: it must be able to predict changes in children's occupations as a result of transfers conditional on school attendance, taking account of the opportunity costs of schooling in terms of forgone earnings. Simultaneity concerns are alleviated by the fact that only predicted –rather than actual – earnings are used on the RHS of the Multinomial logit model. Selection issues into the sample for which the earnings equation is estimated are difficult to address. We follow Bourguignon et.al. (2001) in being skeptical of the Lee (1983) model for multivariate selection bias correction. A bivariate Heckman correction procedure was tried, but abandoned because (a) it was inconsistent with a trivariate model of occupational choice, such as (10), and (b) the estimated coefficients of the Mills ratios had values which were difficult to interpret. This part of the model draws heavily on Bourguignon, Ferreira and Leite (2002b), where specification and estimation are discussed in greater detail.

exercise is forward-looking, we take the 1999 distribution as the base, on which we implement the simulations.

Policy Scenario One is an increase in individual educational endowments.[20] To simulate this increase, we depart from the existing 1999 PNAD data base to construct a 2015 counterfactual data-base. If one had panel data, or even many repeated cross-sections from which to construct pseudo-panels, one might try to analyze the educational, fertility and occupational dynamics of different cohorts, and to predict how these cohorts might behave in 2015. Such longitudinal data is not available to us and, even if it were, we would still be faced with missing observations for the young in 2015.

Instead, we make some adjustments to the 1999 data base. For individuals aged 35 or older, we predict education in the counterfactual (2015) data base, using equation (11) and their actual residuals, but replacing their age by their age minus sixteen. The effect of this operation is to replace each of these persons by individuals with identical observed and unobserved characteristics, but with educational levels prevailing in the cohort which was sixteen years younger in 1999.

For individuals aged 18 to 34 – i.e. those who would have been two to eighteen in 1999, we simulate an educational expansion which increases mean years of schooling in the population (five years or older) at the same annual rate (2.34% p.a.) as was observed between 1990 and 1999. This is done by shifting the cut-off points in the ordered probit model from their estimated values (see Table A5) to the right by a constant, until the average predicted mean years of schooling changed from 5.2 (as observed in 1999) to 7.5 $= (1.0234)^{16} * 5.2$. The educational positions of individuals aged 17 or younger were left unchanged.[21]

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[20] We do not simulate the actual policies which might lead to these increases in educational attainment, such as additional expenditures on school inputs (such as teachers), adoption of school vouchers, and the like. While that would be very interesting, it lies beyond the scope of this paper. We simulate merely the impact (on occupations and incomes) of the *outcomes* of policies which might have generated such increases.

[21] This assumption greatly simplifies the analysis, since it allows us to separate the educational simulation from the occupational choice problem of the young, to which we will turn in Scenarios Two and Three. However, it is probably unrealistic to suppose that the educational preferences of the young would have remained constant in a setting where adults were more educated. The impact of this possible underestimation of schooling amongst the young on household incomes is ambiguous: on the one hand, those who acquired more education and dropped out of school would have been likely to be commanding higher wages. On the other, a number of children would be earning less (from child labor), because of more time spent studying.

These procedures generated counterfactual years of schooling for everyone in our simulated 2015 database. We then feed these counterfactual educational attainments through equations (8)-(9), generating a counterfactual occupational structure and a counterfactual earnings distribution for the population. Once these are aggregated through equation (7), we have created a counterfactual household income distribution for Brazil, which departs from the 1999 distribution, and differs only in ways that reflect well-specified changes in the conditional distribution of educational endowments.

In Table 4 and Figure 4, results of this simulation are presented in two steps, in order to highlight the composition of the effects. Table 4 compares three poverty and four inequality measures for each counterfactual distribution, with those for the actual 1990 and 1999 distributions. Figure 4 plots the differences in the logarithms of mean income per percentile between the counterfactual distributions and the actual 1999 distribution. In both cases, the column (or curve) labeled "α & β" refers to the counterfactual distribution where only the direct impact of changes in education on earnings (through equation 8) is taken into account. The column (or curve) labeled "α, β & λ" refer to the counterfactual distribution where impacts on occupational choice are also included.

The simulated declines in poverty arising from this policy are not large. Mean incomes do rise as a result of greater educational endowments[22] (and of greater induced labor force participation, in the "α, β & λ" simulation), but inequality behaves ambiguously. Whereas the Theil-T and E(2) fall from 1999 to both counterfactual distributions, the Gini and the mean log deviation both rise. This is an example of the inequality-increasing effect which some educational expansions can have when returns to schooling are sufficiently convex.[23] In this case, an increase in unemployment and/or inactivity among the very poor actually causes a further increase in inequality (for two measures) once occupational effects are taken into account. This is very much in line

[22] It is important to note, however, that the returns to education are being kept constant here. This is clearly arbitrary, as changes in the relative supply of skills would in general affect the return structure. On the other hand, this model sheds no light at all on the determinants of the demand for skills, and their prices must be taken as exogenous. Hence, the only alternative in this kind of exercise is to provide some sort of sensitivity analysis by simulating different counterfactuals for different arbitrary return structures. Due to space constraints, we have chosen not to present such an analysis here, but see Ferreira and Leite (2002) for an example.

[23] See Almeida dos Reis and Paes de Barros (1991); Lam (1999) and Bourguignon et. al. (1998) for discussions.

Table 4: Three Policy Scenarios: Simulation Results

	1990	1999	2015 simulated				
			α & β	α, β & λ	τ	t	α, β, λ & t
Mean Income	232.66	254.90	279.10	282.49	255.70	255.78	283.84
Poverty measures							
Poverty Headcount - FGT(0)	7.46%	5.29%	4.98%	5.02%	4.14%	3.87%	3.68%
Poverty Gap - FGT(1)	2.97%	2.50%	2.40%	2.45%	1.91%	1.78%	1.73%
FGT(2)	1.83%	1.77%	1.73%	1.77%	1.30%	1.22%	1.20%
Inequality measures							
Mean of logarithmic deviation - E(0)	0.7416	0.6934	0.7033	0.7065	0.6618	0.6545	0.6672
Theil index - E(1)	0.7663	0.7045	0.6959	0.6956	0.6947	0.6921	0.6836
Half the Coefficient of Variation Squared - E(2)	2.1286	1.5837	1.4922	1.4830	1.5692	1.5665	1.4649
Gini coefficient	0.6119	0.5889	0.5929	0.5933	0.5869	0.5855	0.5875
Net enrollment in primary education (6 to 15 years old)	0.8008	0.9343	0.9343	0.9343	0.9482	0.9464	0.9594
Ratio of girls to boys in primary education (0 to 8 ys)	1.0255	0.9646	0.9314	0.9314	0.9646	0.9608	0.9244
Ratio of girls to boys in secondary education (9 to 12 ys)	1.2695	1.3105	1.1460	1.1460	1.3106	1.3128	1.1414
Ratio of girls to boys in terciary education (13 or more ys)	1.0199	1.3042	1.3308	1.3308	1.3038	1.3038	1.3404
Ratio of women to men in wage employment	0.5550	0.7137	0.7137	0.7548	0.7137	0.7137	0.7548

Source: PNAD/IBGE 1990, 1999 and author's calculation

Key: α & β: Policy Scenario One - Earnings effects only

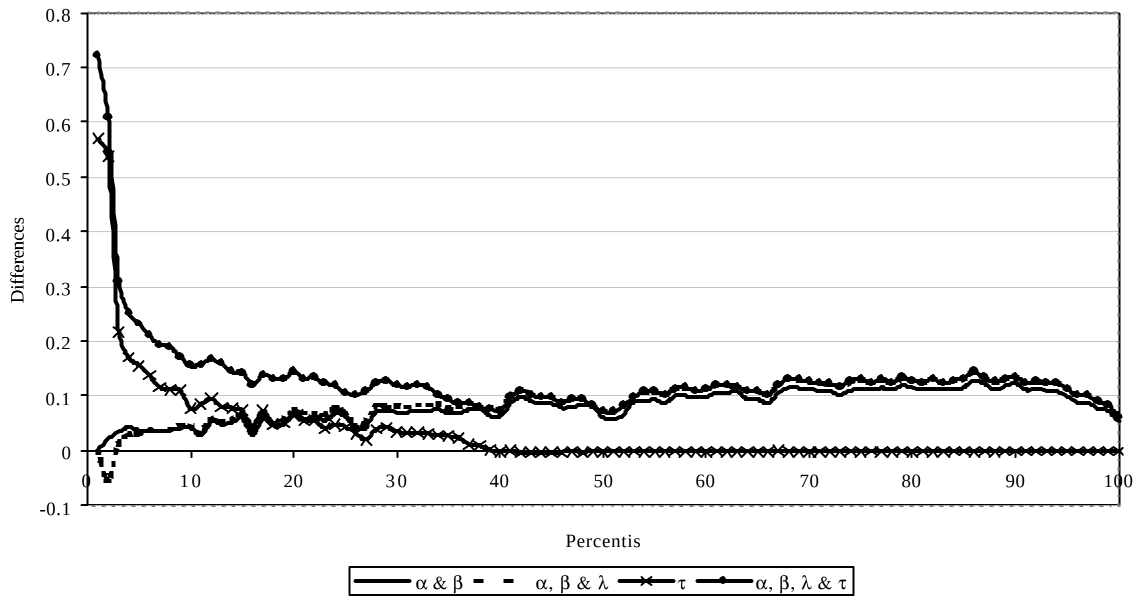
α, β & λ: Policy Scenario One - Earnings and occupational effects

τ: Policy Scenario Two

t: Policy Scenario Three - Transfers Only

α, β, λ & t: Policy Scenario Three - Complete with the result in Ferreira and Paes de Barros (1999) that increases in extreme poverty in urban Brazil between 1985 and 1996 were largely due to an occupational effect at the very bottom of the distribution.

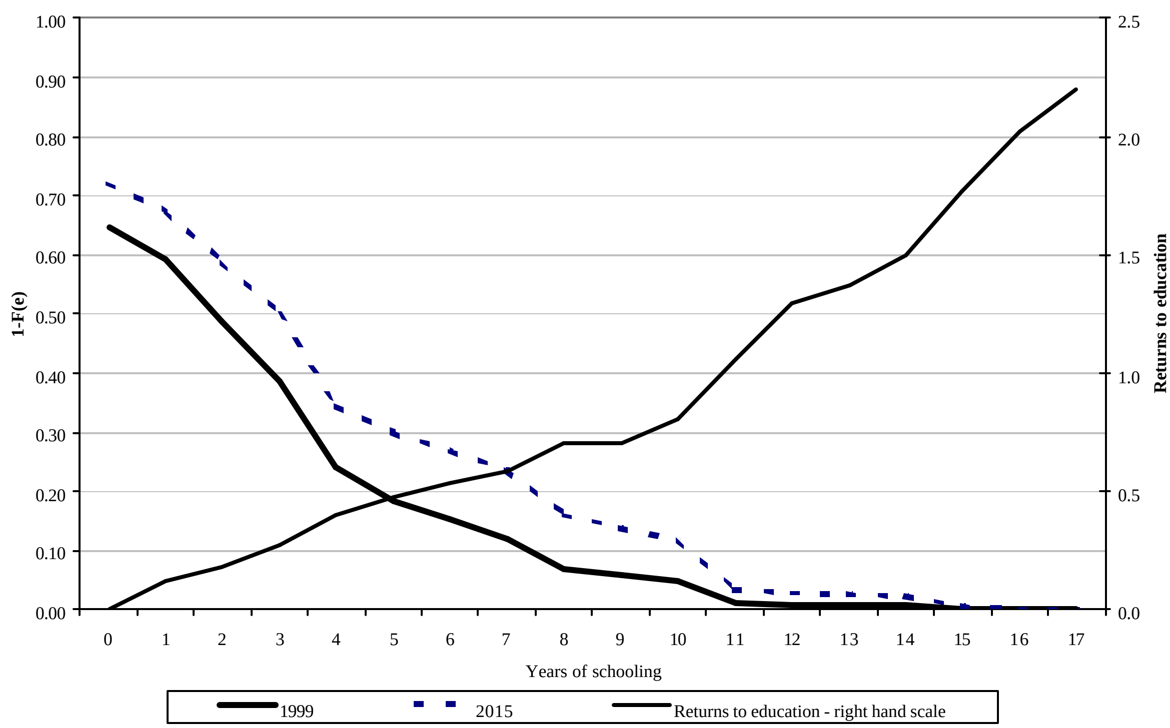
Figure 4: Log Differences Between Counterfactual 2015 and Actual 1999 Distributions



As a result of these effects, the incidence of extreme poverty in Brazil in the simulated distribution falls only from 5.3% to around 5.0% - well short of the Millennium target of 3.73%. The FGT (1 and 2) measures fall even less, proportionately. The implication is that educational expansions in the scale experienced in Brazil in the 1990s are unlikely to be sufficient – on their own – to carry the country through to meeting its MDG first target. Since education is often pointed to as something of a distributional panacea, this is not an entirely irrelevant finding for policy makers.

Why is it that the simulated expansion in education had such a small effect on poverty? The main – but not the only – reason appears to be the flatness of the returns to schooling at very low levels of education (1-4 years), which the poorest people in society tend to have. In Figure 5 we plot (in the solid line) the complement to the cumulative distribution of years of schooling among the poor in Brazil in 1999 – i.e. the bottom 5.29% of the population. The dotted line labeled "2015" plots the counterfactual distribution of schooling for the same individuals, under Policy Scenario One. Using the same horizontal scale, we graph our estimate of the returns to education in Brazil in 1999: the coefficients on year dummies, in a regression of log wages on schooling and all the controls in Table A1, except for the interaction terms between age and education. This model was estimated jointly for employees and self-employed. It shows that almost 80% of the poor (by the international poverty line) in 1999 had four or fewer years of schooling. Even after the counterfactual expansion simulated under Policy Scenario One, still nearly 70% of that group had four or fewer years of schooling. Marginal returns to additional schooling at those levels are very low. The results of the simulation in Column 3 of Table 4, where there are no occupational effects, indicate that these returns are insufficient to make much of a dent in poverty, by any of the three measures reported there. Column 4 indicates that the occupational effect actually contributes to a marginal increase in poverty. This is because the incidence of male unemployment increases with schooling in Brazil and, among the poor, this effect turns out to dominate the increases in female labor force participation due to greater education.

Figure 5: Actual and Counterfactual Distributions of Education (1-F(e)) among the 1999 Poor, and Returns to Schooling



There are a number of important caveats, of course. Returns are being assumed constant – as is the constant term in (8), which might rise with economic growth that arises from other sources. The impact of greater schooling among adults on the demand for education by their children is not taken into account.[24] Perhaps most importantly, gains in per capita incomes through reductions in fertility - which are not being simulated here - can be substantial. In a separate study (Ferreira and Leite, 2002) where it was possible to estimate the impact on household incomes of the reduction in the number of children in households - both directly through reductions in the per capita denominator and indirectly through further increased female labor force participation – this turned out to be substantial. In the simulation most closely comparable to this one, it accounted for just under a quarter of the overall educational impact.[25]

On the other hand, there is no guarantee that the pattern of technical change will allow returns to low skills to rise much, in response to a decline in their supply. Nor has economic growth generally been known to deliver rapid rates of poverty reduction in Latin America. And even if we allowed for an additional fifty percent decline in poverty, due to fertility effects even larger than those estimated in Ferreira and Leite (2002), this would still only have changed the proportional decline in P_0 arising from this policy from 6% to 9%. All in all, it might be wise to pay some heed to the finding that, under reasonable assumptions, educational expansions – however desirable in themselves – will not eradicate poverty in Brazil on their own.

Table 4 also contains information about the other four targets listed in Table 2. The row entitled "Poverty Gap – FGT(1)" contains the second indicator under Goal 1: Poverty and Hunger. Like P_0, this measure also falls very little as a result of the simulated Policy Scenario One. Towards the bottom of the Table, the row on "Net enrollment in private education" shows considerable actual progress between 1990 (80%) and 1999 (93%). Policy Scenario One, as simulated above, does not affect enrollment rates in 2015 – because it does not alter occupational choices among children. It affects only the

[24] Although this impact is incorporated in Policy Scenario Three below and although it wouldn't affect *incomes* in 2015 in any case, except through the labor earnings of under-18s.

[25] Fertility effects could be simulated there because that was a pure "comparative statics" exercise, with no cohort linkages between the counterfactual and the base distributions. Here, with only sixteen years separating 1999 from 2015, a sensible simulation of fertility effects would have had to take cohort effects into account. As discussed, the absence of panel or pseudo-panel data prevents us from undertaking cohort analyses in this exercise.

distribution of education among adults. This is why the two columns corresponding to Policy Scenario One show no change in net enrollment from 1999. We will return to this indicator in the other two simulations.

The next three rows in Table 4 give the ratios of female to male students enrolled in each of the three levels in the Brazilian education system, in accordance with indicator #9 (Goal 3) in Table 2. Between 1990 and 1999, women increased their enrollment advantage over men in both the secondary and tertiary levels, but lost in the primary level. Given that repetition rates are higher for males in primary school (see Bourguignon, Ferreira and Leite, 2002b) this might simply reflect a larger number of male grade-repeaters in primary school. Alternatively, it might signal some deeper trend among young girls. An investigation of this issue goes beyond the scope of this paper, but would deserve attention among those concerned with meeting the gender equality goal in Brazil. If one assumes that gender *equality* is really the goal, the female advantage at the secondary and university levels is cause for concern. Are Brazilian men becoming an undereducated substratum of the population? Can the causes of higher rates of drop-out among men – which may be related to child-labor, drug-trafficking and violence – be combated somehow?

Finally, the row entitled "ratio of women to men in wage employment" approximates the indicator #11, under Goal 3. It is only an approximation because we have not confined the analysis to the non-agricultural sectors. Once again, the historical gain in female employment in the 1990s is rather remarkable, as the ratio climbs from 56% to 71%. Looking forward to 2015, the occupational response to the educational gains simulated under Policy Scenario One would further increase this ratio to just over 75%.

Since an educational expansion appears to be insufficient to meet the MDG poverty-reduction goals, largely because it fails to raise incomes at the very bottom of the distribution, we turn next to a consideration of more direct redistribution. Policy Scenario Two consists of an increase in targeted transfers. Here, rather than simulating a lump-sum transfer to the poorest households in the sample – which would have ignored the practical problems of identifying and reaching them - it seemed more interesting to simulate an existing transfer program, which has received considerable attention and has recently been expanded as a Federal program, namely the *Bolsa Escola*.[26] This is done by adding conditional cash transfers of T = R$15 per child per month (up to a maximum of R$45 per household) to all households whose children between the ages of 6 and 15 are in regular attendance at a public school, provided that the household's pre-transfer income per capita level is less than Y^0 = R$90 per month.[27]

The conditional nature of the transfer is not innocuous in terms of the estimation procedure. There are now five different reduced-form utility levels in the associated multinomial logit model, to be estimated by (10). These are given by (12), with j = 0 denoting occupational category "not attending school"; j =1 denoting "attending school and working", and j = 2 denoting "attending school only". Notation in that equation is exactly as in (10), and M is a part-time adjustment factor for the potential wage of children who both work and study (see Bourguignon et. al., 2002b). Since the standard estimation procedure for a multilogit model involves estimating the differences between parameter values (e.g. α_1 - α_0 or β_2 - β_0), the introduction of incomes which are asymmetric across categories requires additional identification assumptions to enable the estimation of (12). The assumption we make is that individuals working on the market and not going to school (j = 0) have zero domestic productivity. Under this assumptions, the occupational choice model for the young, given by equations (10) and (12) was estimated both for 10-15 year-olds and for 10-18 year-olds (for reasons which will soon become apparent), and the results are presented in Table A4.

[26] Note, however, that the purpose of simulating Policy Scenario Two is to investigate the effects of redistributing current income. Our counterfactual therefore corresponds to a program of redistribution which *starts* in 2015. We do not model the likely impacts of the earlier existence of such a policy (say, during 1999-2015) on additional schooling, or anything else. This is therefore *not* an ex-ante evaluation of Bolsa Escola. For that, please see Bourguignon et. al. (2002b) instead. Other studies describing early versions of the program, and trying to assess their impacts include Rocha and Sabóia (1998), Sant'Ana and Moraes (1997) and World Bank (2001).

[27] These monetary values are kept identical to those adopted in the 2001 law which introduced the Federal *Bolsa Escola* program, under the *Projeto Alvorada*. Since our counterfactual 2015 distribution uses 1999 Reais as units of account, this should not be a problem. Note also that administrative targeting of the benefit does not actually rely on monthly income (of R$90 or less). Instead, in practice a household living standards questionnaire (often supplemented by a visit by a social worker) is used to generate a score, which is calibrated to bear some resemblance to the income means-test. In our simulations, however, we do use the PNAD total income variable for the means-test. This follows Bourguignon, Ferreira and Leite (2002b).

$$
(12)\qquad
\begin{aligned}
&U_i(0) = Z_i.g_0 + a_0 Y_{-I} + b_0 w_i + v_{i0} \\
&U_i(1) = Z_i.g_1 + a_1(Y_{-I} + T) + b_1 w_i + v_{i1} \quad \text{if } Y_{-I} + Mw_i \le Y^{\circ} \\
&U_i(1) = Z_i.g_1 + a_1 Y_{-I} + b_1 w_i + v_{i1} \quad \text{if } Y_{-I} + Mw_i > Y^{\circ} \\
&U_i(2) = Z_i.g_2 + a_2(Y_{-I} + T) + b_2 w_i + v_{i2} \quad \text{if } Y_{-I} \le Y^{\circ} \\
&U_i(2) = Z_i.g_2 + a_2 Y_{-I} + b_2 w_i + v_{i2} \quad \text{if } Y_{-I} > Y^{\circ}
\end{aligned}
$$

One interesting benefit of estimating this structural model for the young is that it allows us not only to simulate the effect of *Bolsa Escola* transfers on incomes, but also on the occupational structure among the young. After all, one objective of conditional cash transfer programs such as this one, *Progresa* in Mexico[28] or PRAF in Honduras, is to encourage human capital accumulation by rewarding school attendance. While this issue is discussed in more detail in Bourguignon, Ferreira and Leite (2002b), we present the main results for the 10-15 age group below, in Table 5. This table contains two occupational transition matrices – one for all households and one for poor households only. Each cell (i, j) in any one of these matrices gives the proportion of people moving from (actual) occupational category i to (counterfactual) occupational category j. The matrix converts the initial (1999) marginal occupation distribution (in the last column) into the counterfactual (2015) marginal distribution (in the bottom row).

Table 5: Simulated effect of Bolsa Escola on schooling and working status (all children 10-15 years old)

	All Households			
	Not Studying	Working and Studying	Studying	Total
Not Studying	64.1%	12.3%	23.7%	6.0%
Working and Studying	-	98.8%	1.2%	16.8%
Studying	-	-	100.0%	77.2%
Total	3.8%	17.4%	78.8%	100.0%
	Poor Households			
	Not Studying	Working and Studying	Studying	Total
Not Studying	38.7%	20.1%	41.2%	8.7%
Working and Studying	-	99.2%	0.8%	30.1%
Studying	-	-	100.0%	61.2%
Total	3.4%	31.6%	65.0%	100.0%

Source: PNAD/IBGE 1999 and author's calculation

[28] Due to the random nature of village selection in the first stage of its beneficiary selection design, *Progresa* - which has been renamed "*Oportunidades*" and is ongoing in Mexico – has been comprehensively evaluated. See, for example, Parker and Skoufias (2000) and Schultz (2000).

It can be observed that the simulated impact of this transfer scheme is to reduce the number of children not enrolled in school by 36% among all households, and by over 60% among poor households. About a third of these individuals will attend school but also keep working in the market. The remaining two thirds would counterfactually only attend school. Movement from the "working and studying" category to the "studying only" category is negligible in both groups. The impact of Policy Scenario Two on incomes can be gauged from Table 4 (column 5), and from Figure 4 (τ line). The small change in mean income reported here is a result of the fact that our model is not an equilibrium one, and we have not increased taxation anywhere to pay for the transfers. Even under this unrealistic "manna from heaven" assumption, the increase in the mean is negligible, due to the small size of the actual *Bolsa Escola* transfers.[29] Their targeting is effective, however, so that even these small transfers reduce inequality by much more than Policy Scenario One, according to every measure but the E(2), which is very sensitive to top incomes. All three poverty measures also fall considerably. The incidence measure P_0 reaches 4.14%, much closer to the MDG target than under Policy Scenario One. Once again, however, it appears that the *Bolsa Escola* policy by itself - even if fully implemented in every state of the Federation, and with an administrative targeting scheme which successfully identified those families living under the R$90 means-test – would not suffice to meet the MDG poverty reduction target for Brazil.

As a natural next step we simulate, as Policy Scenario Three, a combination of the previous two policies: an educational expansion identical to Policy Scenario One, and a transfer scheme with exactly the same criteria and means-test as Bolsa Escola. This time, however, we solve for the transfer amount, so as to meet the MDG poverty reduction target. In other words, we construct a counterfactual income distribution applying the model (7)-(12) to the original 1999 PNAD data set, iterating upwards on the value of the per-child transfer T (in equation 12), until the poverty incidence P_0 for the counterfactual distribution reaches or falls below 3.73%.[30] Remarkably, the value of the individual per-

[29] As noted by one of the referees, the simulation of Policy Scenario One suffers from the same lack of fiscal closure, since we do not account for the need to pay for the costs of additional schooling.

[30] To be consistent, this combination required that the years of schooling variables for both youngsters and their parents which are used in the simulation of (10) be adjusted to reflect gains in educational endowments arising from Policy Scenario One. Similarly, parental occupation variables had to be adjusted to account for changes induced by the simulated occupations in (9).

child transfer which enables the counterfactual distribution to reach the poverty target was exactly T = R$15, just as in the current program. However, the transfer design in our Policy Scenario Three differs from the current *Bolsa Escola* design in two ways: first, there is no household transfer ceiling; second, youngsters in the 16-18 age range are also eligible.[31]

The results for poverty and inequality are given in the last two columns of Table 4, and by the "α, β, λ & τ" line in Figure 4. Column 6 in Table 4 (labeled "t") corresponds to the counterfactual distribution under the modified transfer scheme (i.e. as in τ, but expanded to 16-18 year-olds, and with no benefit ceiling), *without* the educational expansion. It shows that the expansion of the original Bolsa-Escola design further reduces both poverty and inequality, bringing the P_0 indicator to 3.87% - very close to the MDG target. When an educational expansion as described under Policy Scenario One is then further combined with this transfer scheme, poverty incidence finally falls to 3.68%, just below the MDG target. The poverty gap ratio and FGT (2) also fall substantially from 1990, but by less than 50%.

In terms of inequality, the counterfactual Gini coefficient under Policy Scenario Three is almost unchanged with respect to the actual 1999 coefficient. Most of the poverty-reduction effect came from changes at the very bottom of the distribution, as can be seen from the more pronounced fall in the mean log deviation, which is more sensitive to these incomes, and from the "α, β, λ & τ" line in Figure 4. This line shows clearly that the largely proportional gains from Policy Scenario Three accrue exactly to the bottom five percent of the population – exactly the group which was overlooked by the educational expansion under Policy Scenario One.

Gains elsewhere in the distribution, and particularly from the second quintile upwards, are much more like those from Policy Scenario One. This is because the transfer component of Policy Scenario Three is well targeted, as in the real *Bolsa Escola* program, and hence has almost no impact above that range of the income distribution.

[31] The maximum transfer to a single household was R$150, indicating that ten children in this household attended school in the counterfactual distribution. The average transfer per household, among those receiving positive transfers (6,838,017 households in the expanded sample), was R$36.70. Note also that the inclusion of 16-18 year-olds corresponds roughly to the extension of the benefit to secondary schools, which many commentators have suggested. See World Bank (2001) and Camargo and Ferreira (2001).

The transfers do, however, have a sizeable impact on the schooling decisions of those children at which they are aimed. Table 6 below is a counterfactual transition matrix analogous to Table 5, but for 10-18 year-olds. Now that the transfers are combined with higher schooling levels for both students (particularly at the higher ages) and parents, the number of children entering school is even higher than before: over 50% among all households, and 65% among the poor.

Table 6: Simulated effect of Bolsa Escola on schooling and working status (all children 10-18 years old) after simulations

	All Households			
	Not Studying	Working and Studying	Studying	Total
Not Studying	45.8%	26.9%	27.3%	14.2%
Working and Studying	-	95.3%	4.7%	22.3%
Studying	-	1.9%	98.0%	63.6%
Total	6.5%	26.3%	67.2%	100.0%
	Poor Households			
	Not Studying	Working and Studying	Studying	Total
Not Studying	36.5%	30.6%	32.8%	15.4%
Working and Studying	-	96.8%	3.2%	31.2%
Studying	-	0.6%	99.4%	53.4%
Total	5.6%	35.2%	59.1%	100.0%

Source: PNAD/IBGE 1999 and author's calculation

Mobility from the “working and studying” category to the “studying only” category is also higher than before, but still not substantial. Interestingly, the educational gains which are incorporated into this counterfactual mean that it is now possible to have people moving in the reverse direction: from studying only to both working and studying. This arises because one does not lose one’s entitlement to the transfer, and the multinomial logit model indicates that, with the additional education level, this individual would most likely now also be working.

The total annual cost of the transfers disbursed under the counterfactual Policy Scenario Three would have been approximately R$ 3 billion, always in 1999 prices. This amount excludes any administrative costs, as well as the costs of implementing the educational reform policies underlying the increases in schooling simulated as in Policy Scenario One. It corresponds to 0.31% of the Brazilian GDP in 1999.

4. Conclusions

In this paper, we have sought to investigate whether micro-simulation techniques can shed any light on the kinds of policies which might help countries reach their Millennium Development Goals. Rather than trying to cover many countries superficially, the approach we adopted was to test a richer set of approaches for a single country. We picked Brazil, with which we are most familiar. We started out in Section 2 with a simple statistical procedure, based on different combinations of growth rates and inequality reductions which would be consistent with the poverty reduction target. This exercise suggested that, at least for a country as unequal as Brazil, the MDG poverty reduction target could be attained through a modest reduction in inequality, but would require a growth rate well above the recent historical average if the Lorenz curve remained unchanged. Unless Brazil's growth performance improves considerably over the next decade (with respect to the 1990s), then some amount of redistribution will be required to ensure that the Millennium Development Goal poverty reduction target is met. Additionally, if that redistribution were to be accomplished through a universal lump-sum transfer – rather than through more targeted interventions – its financing would imply a sizable additional fiscal effort.

While this is a useful general policy message, the 'statistical' approach adopted in Section 2 was too aggregated for thinking about specific policies, be they for education, labor markets, redistribution schemes, or what have you. Additionally, the underlying assumption of the specific form in which inequality was reduced in that particular simulation – which we called Lorenz-convex inequality reduction – turned out to be strong. In Brazil, the fall in the Gini coefficient actually observed between 1990 and 1999 – in conjunction with the observed growth rate - would have been enough to more than meet the MDG. Nevertheless, the country's observed poverty incidence in 1999 was still well above the target – because the shift in the Lorenz curve which generated that reduction in the Gini was nothing like the simulated one.

This persuaded us of the need to employ a structurally richer model of household income determination, which was presented in Section 3, and included parametric models for earnings, occupational and educational distributions, conditional on a number of observed individual and household characteristics. On the basis of these estimated models, we simulated three different policy scenarios on the 1999 PNAD data base, attempting to construct plausible outcomes for 2015. Policy Scenario One consisted of an increase in the schooling levels of the population, calibrated to be consistent with the increases observed over the 1990s. Policy Scenario Two was the federal Bolsa Escola program, as currently designed, as if it were functioning country-wide. Policy Scenario Three was a combination of the previous two, with a limited expansion in the coverage of the transfer benefit.

Throughout, we attempted to keep the limitations of the exercise and the strength of the assumptions underlying it at the forefront. Even in these simulations, which take existing behavioral patterns into account to a much greater extent, we are unable to predict how prices – and the prices of skills in the labor market in particular – will respond to the changes we simulate. Or indeed to all the other myriad changes which we do *not* simulate, and have no idea about. This abstraction from equilibrium responses is a general characteristic of simulations in the Oaxaca (1973); Blinder (1973) family.[32] But it is less problematic when used in the context for which it was originally designed, namely to decompose changes that have already happened and been observed into different effects. In the present context, when a single structure is observed and used to construct an entire counterfactual in the future, the limitations are very serious indeed.

Nevertheless, some of the findings from our Section 3 simulations were interesting. First, an expansion in schooling levels appears to be unlikely to reduce extreme poverty by very much, because returns to an additional year of schooling at very low levels of education are too small. Educational expansions are enormously beneficial to society as a whole, but their impacts on the poorest of the poor are likely to be indirect, and could take a very long time to be felt. If policy-makers in a country like Brazil were serious about reducing the incidence and severity of extreme poverty, it seems almost certain that they should rely on some form of redistribution.

[32] See DiNardo, Fortin and Lemieux (1996) and Bourguignon, Ferreira and Leite (2002a) for discussions.

In that context, a conditional cash-transfer program, like *Bolsa Escola* or *Progresa*, designed with incentive considerations very much in mind, would appear to be a natural candidate. Our simulations indicate that, whereas a program like *Bolsa Escola* might not be sufficient in isolation and in their current format, it might be a very important tool in meeting the Millennium Development Goals, if combined with a set of sustained policies aimed at expanding educational attainments. Our Policy Scenario Three, which could be described as a *Bolsa Escola* extended to secondary school and without household ceilings, combined with an educational expansion at the pace which was observed historically in Brazil during the 1990s, does generate a counterfactual distribution where the incidence of poverty is below the MDG target for the country. And because it is narrowly targeted to the poor, its fiscal requirements are an order of magnitude smaller than those of a universal lump-sum redistribution scheme such as that implied by equation (1) in Section 2: 0.3% - rather than 3% - of GDP.

Of course, because prices might change; because occupational structures might no longer be governed by the parametric relationships estimated in 1999; and because of a million other unforeseen events, these are not predictions. Our scenarios are not intended - and should never be taken - as detailed policy blueprints. But they may, perhaps, be useful as an indication of the broad types of policies which policy makers might want to focus on, if they are interested in reducing extreme poverty in unequal middle-income countries.

It turns out that the extreme poor in these countries are hard to reach through “blunt” policy instruments like generalized educational expansions. Distribution-neutral economic growth – which certainly is good for the poor – also needs to be of some magnitude to translate into the absolute income increments needed to raise those at the very bottom of the distribution above the relevant poverty lines. If such copious growth is for some reason not immediately forthcoming, “sharper” tools - like fiscally affordable targeted conditional redistribution programs - can become very useful complements to broad-based educational and income expansions.

References.

Almeida dos Reis, José G. and Ricardo Paes de Barros (1991): "Wage Inequality and the Distribution of Education: A Study of the Evolution of Regional Differences in Inequality in Metropolitan Brazil", *Journal of Development Economics*, **36**, pp. 117-143.

Blinder, Alan S. (1973): "Wage Discrimination: Reduced Form and Structural Estimates", *Journal of Human Resources*, **8**, pp.436-455.

Bourguignon, F. (2002): "The Growth Elasticity of Poverty Reduction: explaining heterogeneity across countries and time periods", in T. Eicher and S. Turnovski (eds.): *Growth and Inequality*, (Cambridge, MA: MIT Press).

Bourguignon, F., F.H.G. Ferreira and P.G. Leite, (2002a): 'Beyond Oaxaca-Blinder: Accounting for Differences in Household Income Distributions across Countries', World Bank Policy Research Working Paper 2828 (April).

Bourguignon, F., F.H.G. Ferreira and P.G. Leite (2002b): "Ex-Ante Evaluation of Conditional Cash Transfer Programs: the Case of Bolsa Escola", World Bank Policy Research Working Paper 2916 (October).

Bourguignon, F., F.H.G. Ferreira and N. Lustig, (1998) 'The Microeconomics of Income Distribution Dynamics in East Asia and Latin America' (mimeo), World Bank, DECRA: Washington DC.

Bourguignon, F.; M. Fournier and M. Gurgand (2001): "Selection Bias Correction Based on the Multinomial Logit Model", Working Paper #20023-04, CREST/INSEE, Paris.

Camargo, J. M. and F.H.G. Ferreira (2001): "O Beneficio Social Único: uma proposta de reforma da política social no Brasil", Discussion Paper #443, Departamento de Economia, Pontifícia Universidade Católica, Rio de Janeiro.

Datt, G. and M. Ravallion (1992): "Growth and Redistribution Components of Changes in Poverty Measures: a Decomposition with Applications to Brazil and India in the 1980s", *Journal of Development Economics*, **38**, pp. 275-295.

Deaton, A (1997): *The Analysis of Household Surveys: A Microeconomic Approach to Development Policy*, (Baltimore: Johns Hopkins University Press ISBN 0-8018-5254-4)

DiNardo, John, Nicole Fortin and Thomas Lemieux (1996): "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-Parametric Approach", *Econometrica*, **64** (5), pp.1001-1044.

ECLAC and UNDP (forthcoming): "Meeting the Millennium Poverty Reduction Targets in Latin America", report prepared jointly by the UNDP, ECLAC and IPEA, Brazil.

Ferreira, F.H.G., Barros, R. (1999) "The Slippery Slope: Explaining the Increase in Extreme Poverty in Urban Brazil; 1976-96", *Revista de Econometria*, **19** (2): 211-96.

Ferreira, F.H.G., P. Lanjouw and M. Neri (forthcoming): "A Robust Poverty Profile for Brazil Using Multiple Data Sources", *Revista Brasileira de Economia*, **57** (2) (April-June 2003).

Ferreira, F.H.G. and P.G. Leite (forthcoming): "Educational Expansion and Income Distribution: A micro-simulation for Ceará", Chapter 11 in R. van der Hoeven and A. Shorrocks (eds.) *Growth, Inequality and Poverty*, (Helsinki: WIDER).

Foster, J.E., J. Greer and E. Thorbecke (1984): "A Class of Decomposable Poverty Indices", *Econometrica*, **52**, pp.761-766.

Kakwani, N. (1980): "On a Class of Poverty Measures", *Econometrica*, **48** (2) pp. 437-46.

Kakwani, N. (1993): "Poverty and Economic Growth with Application to Côte d'Ivoire" *Review of Income and Wealth*, **39**, pp.121-139.

Lee, L. F. (1983): "Generalized Econometric Models with Selectivity", *Econometrica*, **51**, pp.507-512

Oaxaca, Ronald (1973): "Male-Female Wage Differentials in Urban Labor Markets", *International Economic Review*, **14**, pp.673-709.

Parker, S. and E. Skoufias (2000): "The Impact of Progresa on Work, Leisure and Time Allocation", *IFPRI Final Report on Progresa*, IFPRI, Washington, DC.

Ravallion, M. (1997): "Can High-Inequality Developing Countries Escape Absolute Poverty?", *Economics Letters*, **56**, pp. 51-57.

Ravallion, M. (2000): "On Decomposing Changes in Poverty into 'Growth' and 'Redistribution' Components", *Journal of Quantitative Economics*, **16** (1), pp. 105-118.

Rocha, S. and J. Sabóia (1998): "Programas de Renda Mínima: Linhas Gerais de uma Metodologia de Avaliação", Discussion Paper #582, IPEA/UNDP, Rio de Janeiro.

Sant'Ana, S.R. and A. Moraes (1997): *Avaliação do Programa Bolsa Escola do GDF*, (Brasília: Fundação Grupo Esquel Brasil).

Schultz, T. Paul (2000), “The Impact of Progresa on School Enrollment”, *IFPRI Final Report on Progresa*, IFPRI, Washington, DC.

Tsui, K. (1996): “Growth-Equity Decomposition of a Change in Poverty: An Axiomatic Approach”, *Economics Letters*, **50**, pp.417-423.

World Bank (2001): *Brazil: An Assessment of the Bolsa Escola Programs*, Report 20208-BR, Washington, DC.

World Bank (2002): *World Development Report 2003: Sustainable Development in a Dynamic Worl*d, (New York: Oxford University Press).

Appendix.

Equation (4) can be obtained as follows. We know that the Gini Coefficient is given by:

$$G(y) = \frac{1}{2n^2 m_y} \sum_i \sum_j \left| y_i - y_j \right|$$

It follows from (1) that: $|y_i^* - y_j^*| = (1+ß)(1-a)|y_i - y_j|$

Thus: $??\ |y_i^* - y_j^*| = (1+ß)(1-a)??|y_i - y_j|$

Dividing through by $2n^2(1+ß)\mu_y$:

$$(2n^2\mu_y^*)^{-1}\ ??\ |y_i^* - y_j^*| = (2n^2(1+ß)\mu_y)^{-1}(1+ß)(1-a)??|y_i - y_j|$$

which yields equation (4).

Table A1: Micerian Equation for adults (above 18 years old)

	Self-employed and Employer			Employees: Formal, informal and public servants		
	Coefficient	Std	P>|z|	Coefficient	Std	P>|z|
R^2	0.52			0.59		
#obs	39,071			81,918		
Years of schooling						
1	0.0805	0.0281	0.0040	-0.0086	0.0158	0.5840
2	0.1646	0.0245	0.0000	-0.0465	0.0131	0.0000
3	0.2202	0.0245	0.0000	-0.0332	0.0130	0.0100
4	0.3603	0.0251	0.0000	-0.0089	0.0128	0.4880
5	0.4145	0.0327	0.0000	0.0024	0.0156	0.8760
6	0.4470	0.0368	0.0000	0.0052	0.0177	0.7710
7	0.5210	0.0392	0.0000	-0.0214	0.0188	0.2540
8	0.5732	0.0393	0.0000	0.0416	0.0192	0.0300
9	0.5296	0.0548	0.0000	0.0302	0.0229	0.1860
10	0.6555	0.0505	0.0000	0.0495	0.0234	0.0350
11	0.8045	0.0482	0.0000	0.2230	0.0228	0.0000
12	0.9970	0.0890	0.0000	0.4566	0.0316	0.0000
13	1.0622	0.0756	0.0000	0.4579	0.0337	0.0000
14	1.0457	0.0796	0.0000	0.5351	0.0343	0.0000
15	1.3055	0.0697	0.0000	0.6911	0.0331	0.0000
16	1.4778	0.0758	0.0000	0.8992	0.0380	0.0000
17	1.7109	0.0986	0.0000	0.9884	0.0468	0.0000
Age	0.0526	0.0024	0.0000	0.0468	0.0013	0.0000
Age2	-0.0006	0.0000	0.0000	-0.0006	0.0000	0.0000
Interaction between age and schooling	0.0005	0.0001	0.0000	0.0014	0.0001	0.0000
Male	0.6702	0.0110	0.0000	0.4595	0.0046	0.0000
White	0.2250	0.0106	0.0000	0.1368	0.0048	0.0000
Area						
Urban non-metropolitan	-0.1539	0.0109	0.0000	-0.1971	0.0048	0.0000
Rural	-0.4709	0.0145	0.0000	-0.3768	0.0075	0.0000
Occupation						
Self employed	-0.8164	0.0141	0.0000			
Formal				-0.0260	0.0077	0.0010
Informal				-0.4102	0.0085	0.0000
Region						
North	-0.1356	0.0181	0.0000	-0.0844	0.0093	0.0000
Northeast	-0.4507	0.0128	0.0000	-0.3696	0.0059	0.0000
South	-0.1220	0.0138	0.0000	-0.0783	0.0062	0.0000
Center-West	-0.0044	0.0160	0.7840	-0.0199	0.0068	0.0040
Intercept	4.4372	0.0634	0.0000	4.4388	0.0314	0.0000

Source: PNAD/IBGE 1999 and author's calculation

Table A2: Earnings Equation for the Young

	10 to 15 years old[1]			10 to 18 years old[2]		
	Coefficient	Std	P>|z|	Coefficient	Std	P>|z|
n obs	2428			8637		
R^2	0.48			0.51		
Dummy WS	-0.2956	0.0335	0.0000	-0.1293	0.0147	0.0000
Years of schooling	-0.0483	0.0192	0.0120	-0.0128	0.0085	0.1300
Age	0.1538	0.0118	0.0000	0.1464	0.0047	0.0000
Years of schooling^2	0.0095	0.0020	0.0000	0.0042	0.0007	0.0000
Male	0.1590	0.0273	0.0000	0.2210	0.0140	0.0000
White	0.0844	0.0277	0.0020	0.0752	0.0144	0.0000
Urban non metroplitan	0.0341	0.0315	0.2800	-0.0815	0.0152	0.0000
Rural	0.0334	0.0393	0.3940	-0.1197	0.0205	0.0000
North	-0.1806	0.0440	0.0000	-0.0720	0.0255	0.0050
Northeast	-0.1984	0.0365	0.0000	-0.1941	0.0202	0.0000
South	-0.0280	0.0403	0.4860	-0.0470	0.0183	0.0100
Center-West	-0.1189	0.0397	0.0030	-0.0837	0.0196	0.0000
Log of means earnings by cluster	0.3725	0.0141	0.0000	0.3580	0.0097	0.0000
Intercept	1.3783	0.1745	0.0000	1.1375	0.0892	0.0000

Notes:
[1] - Log of means earnings by cluster computed for children between 10 to 15
[2] - Log of means earnings by cluster computed for children between 10 to 18
Source: PNAD/IBGE 1999 and author's calculation

Table A3: The Multinomial Logit Estimates for Participation Behavior and Occupational Choice for adults (above 18 years old)

	Self-employed		Formal		Informal		Public servants		Employers	
	ME*	P>|z|	ME*	P>|z|	ME*	P>|z|	ME*	P>|z|	ME*	P>|z|
Pseudo R^2	0.1798									
# obs	210,000									
Years of schooling	-	0.000	-	0.000	-	0.121	-	0.000	-	0.000
Years of schooling2	-	0.730	-	0.416	-	0.000	-	0.008	-	0.058
Age	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000
Age2	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000
Interaction between age and schooling	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000
Male	0.155	0.000	0.084	0.000	0.018	0.000	0.005	0.000	0.043	0.000
White	0.013	0.000	-0.008	0.060	-0.020	0.000	-0.009	0.000	0.017	0.000
Average endowments of age	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.662	0.000	0.000
Average endowments of schooling	0.000	0.642	-0.003	0.000	-0.006	0.000	-0.001	0.000	0.002	0.000
# of households member below 18 years old	0.004	0.000	-0.005	0.000	0.005	0.000	0.000	0.276	0.000	0.873
# of households member between 19 and 64 years old	-0.011	0.000	0.006	0.000	-0.005	0.000	-0.001	0.278	-0.002	0.000
# of households member above 65 years old	0.005	0.081	-0.026	0.000	-0.020	0.000	-0.003	0.109	0.009	0.000
Head of the household	0.186	0.000	0.190	0.000	0.070	0.000	0.046	0.000	0.053	0.000
2nd head of the household	0.031	0.000	-0.079	0.000	-0.074	0.000	0.006	0.001	0.016	0.000
If not the head, the head is active?	0.002	0.178	-0.030	0.000	-0.006	0.000	-0.005	0.000	0.010	0.000
Area										
Urban non-metropolitan	0.021	0.000	-0.014	0.049	0.026	0.000	0.020	0.000	0.016	0.000
Rural	0.070	0.000	-0.105	0.000	0.015	0.000	0.009	0.000	0.018	0.000
Region										
North	0.040	0.000	-0.176	0.000	-0.021	0.629	0.025	0.000	0.001	0.010
Northeast	0.068	0.000	-0.126	0.000	-0.020	0.000	0.014	0.000	0.003	0.001
South	0.026	0.000	0.016	0.000	-0.015	0.000	0.002	0.348	0.002	0.047
Center-West	0.000	0.011	-0.065	0.000	0.018	0.000	0.021	0.000	0.007	0.000
Intercept	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000

Source: PNAD/IBGE 1999 and author's calculation

Note: ME*: Marginal Effect calculated from the estimated coefficients.

The marginal effects for age and education are omitted due to the interaction terms.

Table A4: The Multinomial Logit Estimates for Participation Behavior and Occupational Choice for the Young

	Pseudo-R^2	#obs	Working and Studying ME*	Working and Studying P>|z|	Studying ME*	Studying P>|z|
10 to 15 years old	0.2145	43418				
Total household income			0.000	0.065	0.000	0.000
Earning's children (What)			0.002	0.001	-0.004	0.000
Total people by household			0.009	0.000	-0.007	0.196
Age			-	0.000	-	0.000
Years of schooling			-	0.000	-	0.000
$(\text{Age-schooling})^2$			-	0.001	-	0.091
White			-0.028	0.997	0.038	0.000
Male			0.101	0.000	-0.087	0.036
Max parent's education			-0.008	0.000	0.013	0.000
Max parent's age			-0.001	0.403	0.001	0.000
Number of children (0 to 5 years old)			-0.001	0.000	-0.010	0.000
Rank of child			0.014	0.219	-0.014	0.546
Urban non metroplitan			0.031	0.015	-0.032	0.451
Rural			0.212	0.000	-0.219	0.000
North			0.093	0.000	-0.084	0.742
Northeast			0.094	0.000	-0.076	0.006
South			0.095	0.023	-0.117	0.000
Center-West			0.069	0.002	-0.075	0.026
Means of earnings by cluster			-0.002	0.000	0.004	0.000
Intercept			-0.729	0.000	1.216	0.000
10 to 18 years old	0.2557	65507				
Total household income			0.00	0.07	0.00	0.00
Earning's children (What)			0.00	0.02	0.00	0.00
Total people by household			0.01	0.00	0.00	0.00
Age			-	0.00	-	0.00
Years of schooling			-	0.00	-	0.00
$(\text{Age-schooling})^2$			-	0.00	-	0.01
White			-0.02	0.55	0.02	0.00
Male			0.08	0.00	-0.08	0.61
Max parent's education			-0.01	0.00	0.01	0.00
Max parent's age			0.00	0.00	0.00	0.00
Number of children (0 to 5 years old)			0.00	0.00	-0.02	0.00
Rank of child			0.01	0.71	-0.02	0.00
Urban non metroplitan			0.03	0.24	-0.04	0.00
Rural			0.18	0.00	-0.22	0.00
North			0.04	0.00	-0.03	0.00
Northeast			0.06	0.00	-0.04	0.00
South			0.07	0.74	-0.10	0.00
Center-West			0.05	0.00	-0.06	0.01
Means of earnings by cluster			0.00	0.22	0.00	0.00
Intercept			-0.77	0.00	1.31	0.00

Source: PNAD/IBGE 1999 and author's calculation

Note: ME*: Marginal Effect calculated from the estimated coefficients.
The marginal effects for age and education are omitted due to the interaction terms.

Table A5: Ordered Probit model (5 years old or more)

			Coefficien	Std	P>|z|
Age group					
	5 to 10		-1.6811	0.0062	0.0000
	11 to 18		-0.0218	0.0040	0.0000
Male			-0.0405	0.0041	0.0000
White			0.3851	0.0045	0.0000
Area					
	Urban non-metropolitan		-0.2275	0.0046	0.0000
	Rural		-0.8049	0.0061	0.0000
Region					
	North		-0.0280	0.0083	0.0010
	Northeast		-0.2405	0.0054	0.0000
	South		-0.0121	0.0058	0.0380
	Center-West		0.0541	0.0067	0.0000
	Cut-off points				
		1	-1.4363	0.0065	
		2	-1.2189	0.0062	
		3	-0.9484	0.0060	
		4	-0.6563	0.0058	
		5	-0.1847	0.0058	
		6	0.0110	0.0057	
		7	0.1627	0.0057	
		8	0.3162	0.0057	
		9	0.5968	0.0058	
		10	0.7002	0.0058	
		11	0.8144	0.0058	
		12	1.4831	0.0063	
		13	1.5423	0.0064	
		14	1.6095	0.0065	
		15	1.6978	0.0067	
		16	2.1622	0.0082	
		17	2.6981	0.0126	

Source: PNAD/IBGE 1999 and author's calculation