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Meeting the Millennium Development Goals in Brazil: Can Microeconomic Simulations Help?

In September 2000, the member states of the United Nations (UN) 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 International Monetary Fund (IMF), the World Bank, and the Organization for Economic Cooperation and Development (OECD), the General Assembly recognized the Millennium Development Goals (MDG) as an integral component of that Declaration. There are eight such goals, each corresponding to a key development aim in one dimension of human welfare. They are as follows: (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; and (8) develop a global partnership for development.

Associated with the eight goals are eighteen specific targets, which quantify the broad goals in a measurable manner. In addition, there are a total of forty-eight indicators, each of which is associated with a specific

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target. These are meant to be monitoring variables, whose evolution can be evaluated to verify progress toward the goals.[1]

These goals and their associated targets and indicators have already succeeded, to a large extent, in at least one of their objectives, namely, raising awareness of the issues that they seek to address. They have also served to impress on national and international policymakers the need to secure measurable progress along various dimensions of human welfare in a relatively short period of time: most targets specify objectives that should be accomplished no later than 2015. As part of the effort, some of the multilateral institutions have set up monitoring programs that 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 arisen 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 by 2015 the incidence of extreme poverty that prevailed in 1990.[2]

This paper investigates whether modern microeconomic simulation techniques can shed any light on the policy options available to countries that want to meet 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

1. For instance, the first goal (to eradicate extreme poverty and hunger) breaks down into two targets: (1) halving, between 1990 and 2015, the proportion of people whose income is less than one dollar a day and (2) halving, between 1990 and 2015, the proportion of people who suffer from hunger. The first target, in turn, lists three indicators to be used to measure progress toward compliance: the proportion of the population whose income is below one dollar a day, the poverty gap ratio, and the share of the poorest quintile in national consumption. For a complete listing of goals, targets, and indicators, see www.developmentgoals.org.

2. This was a simulation exercise for Latin America, undertaken jointly by the United Nations Development Program (UNDP) and the UN Economic Commission for Latin America and the Caribbean (ECLAC), alongside Brazil's Instituto de Pesquisa Econômica Aplicada (IPEA). See ECLAC and UNDP (2002) for a full report.

full account of market adjustments toward equilibrium, or of subsequent agent responses.

Nevertheless, microeconomic-simulation-based social forecasting can provide some valuable lessons. We apply our analysis to a single country—Brazil—and to three of the eight goals. This gives us five indicators to include in the exercise. We list them here using the official number assigned to each in the Millennium Development Goals:

—Goal 1: Poverty and hunger. The indicators used are (1) the proportion of the population whose income is below $1 per day and (2) the poverty gap ratio.

—Goal 2: Primary education. The associated indicator is (6) net enrollment in primary education.

—Goal 3: Gender equality. The indicators are (9) the ratio of girls to boys in primary, secondary, and tertiary education and (11) the ratio of women to men in wage employment in the nonagricultural sector.

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 that are statistically consistent with achieving the first MDG target: halving, between 1990 and 2015, the proportion of people whose income is less than one dollar a day. 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 then turn, in the following section, to an approach that 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 imply that the simulation results should not be understood as predictions.

Growth and Inequality: A Statistical Perspective

The first target associated with the first Millennium Development Goal 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.[3] Since this is a poverty-reduction target, it makes sense to start thinking about it in terms of the two basic ways in which the extent of poverty in any given distribution can be reduced: growth in the mean or reduction in inequality (or both).

A measure of poverty, Π, 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. Poverty is thus always a functional of the distribution of income and of the poverty threshold: $\Pi = \Pi(F(y), z)$. As we just saw, the MDG poverty-reduction target is formulated in terms of the poverty-incidence indicator, P_0, so that this functional is simply $P_0 = F(z)$.[4]

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 established results.[5] Namely,

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

where $L'(p)$ denotes the first derivative of the Lorenz curve,

$$L(p) = \frac{1}{\mu_y}\int_0^{y(p)} xf(x)dx = \frac{1}{\mu_y}\int_0^{p} F^{-1}(p)dp,$$

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

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

Thus,

$$P_0 = L'^{-1}\left(\frac{z}{\mu_y}\right).$$

3. This section draws heavily on ECLAC and UNDP (2002). The methodology presented here was developed originally for the preparation of that report. Both of us were fortunate to work on the team that prepared it, and we are grateful to all other team members, especially Ricardo Paes de Barros, for their guidance.

4. On the definition and properties of the P_α family, see Foster, Greer, and Thorbecke (1984).

5. See, for example, Kakwani (1980); Deaton (1997).

This merely states that the incidence of poverty is completely determined by the poverty line, the mean of the distribution, and its Lorenz curve.[6]

This is useful for investigating 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 exist (a number of) hypothetical distributions F^*, with mean level μ_y^* and Lorenz curve $L^*(p)$, which would have a poverty incidence of $P^* = L^{*\prime -1}(z/\mu_y^*)$.

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

$$(1) \qquad y^* = (1+\beta)[(1-\alpha)y + \alpha\mu_y],$$

with $0 < \alpha < 1$ and $\beta > 0$.

This transformation corresponds to a distribution-neutral increase of 100β percent in everyone's income level, coupled with a redistribution policy in which everyone's income is taxed 100α percent and the revenues are distributed equally across every person in the population.

The mean of the resulting counterfactual distribution would be β percent higher than in the original distribution:

$$(2) \qquad \mu_y^* = (1+\beta)\mu_y.$$

The Lorenz curve of the new distribution would also be transformed:

$$(3) \qquad L^*(p) = (1-\alpha)L(p) + \alpha p.$$

In addition, the Gini coefficient of the counterfactual distribution would, as a result, be 100α percent lower than for the original distribution:[7]

6. This fact has long been known and, indeed, long been used to decompose observed changes in poverty into components stemming from growth and inequality. There is no single right decomposition, and at least three approaches have been proposed, namely, those of 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 analyze sets of arbitrarily defined counterfactual distributions, rather than focusing on decomposing poverty changes between well-defined specific actual distributions.

7. See the appendix for a proof.

$$G^*(y) = (1 - \alpha)G(y). \tag{4}$$

Given these properties, we refer to the two-parameter (α, β) class of transformations of an income distribution, which is given by equation 1, as Lorenz-convex transformations.[8] This is clearly a restrictive set of transformations, but it is analytically convenient and has thus been used before in the literature.[9]

The values of α and β can be chosen so that equations 2 and 3 hold exactly, satisfying $P^* = L^{*\prime -1}(z/\mu_y^*)$. 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 α and β:

$$P^* = P_0(\alpha, \beta, F(y), z). \tag{5}$$

Since α and β 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 α or β (subject to $0 < \alpha < 1$, $\beta > 0$), there will exist a (positive or negative) value of the other parameter such that equation 5 holds. One can thus define an isopoverty set for the distribution $F(y)$ for each target poverty incidence, P^*, with respect to the poverty line, z, as the set of α, β pairs that would lead from $F(y)$ to another distribution with poverty rate P^*. Formally,

$$I(P^*, F(y), z) = \left\{(\alpha, \beta) \middle| P_0(\alpha, \beta, F(y), z) = P^*\right\}. \tag{6}$$

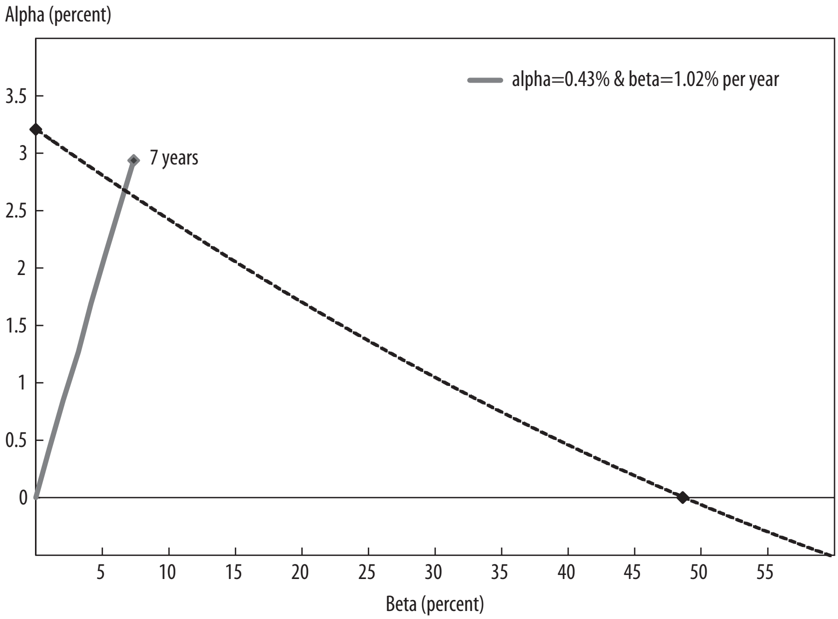
When plotted on α, β space, we refer to this as the P^* isopoverty curve. In the specific case of the MDG poverty reduction target, P^* is simply one-half of the poverty incidence rate, P_0, that prevailed in the country in 1990. In this case, any combination of a rate of inequality reduction (α) and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

Figure 1 plots the isopoverty curve for the Brazilian MDG poverty target, which is defined on the basis of the poverty incidence estimated from the 1990 national household survey *Pesquisa Nacional por Amostra de*

8. Analogously, we call any process that leads from $L(p)$ to $L^*(p)$, defined as in equation 3, for $0 < \alpha < 1$, a Lorenz-convex inequality reduction.

9. It underlies the Kakwani (1993) decompositions, for instance.

FIGURE 1. Brazil's MDG Isopoverty Curve



Domicílios (PNAD).[10] Using a purchasing power parity exchange rate and a thirty-day month, the international dollar-per-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 percent. This implies that the MDG poverty reduction target for Brazil would be to reach an extreme poverty incidence of 3.73 percent 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 it covers the entire country, except the rural areas of the states of Acre, Amapá, Amazonas, Pará, Rondônia, and Roraima. Its sample size in 1990 (1999) was 72,084 (91,546) households. See Ferreira, Lanjouw, and Neri (2003) for a discussion of its shortcomings in measuring incomes, particularly in rural areas, although there is no better dataset for either 1990 or 1999 in Brazil.

11. The international poverty line of one dollar per person per day, which originated from the World Bank Research Department, was originally used in 1990 and was expressed

Figure 1 plots the combination of cumulative rates of growth in mean per capita incomes from 1990 to 2015 (β, on the horizontal axis) and the cumulative rates of Lorenz-convex inequality reduction (α, on the vertical axis) that would achieve that target. Table 1 isolates three specific points for analysis. The first of these (simulation A) 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 percent 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 percent) could be reached with no movement in the Lorenz curve, through an accumulated per capita growth rate of 50 percent—corresponding to an average annual rate of 1.64 percent over the twenty-five-year period—at the horizontal intercept of the curve (simulation B).

In between these pure strategies, there lies a continuum of combinations of inequality reductions and accumulated rates of economic growth that would be consistent with halving Brazil's 1990 poverty incidence. One such combination, which is of some interest, is based on the country's historical performance between 1990 and 1999 (simulation C). Over these nine years, Brazil's mean income, as reported in the PNAD, grew at an average annual rate of 1.02 percent, and the Gini coefficient fell at an average annual rate of 0.43 percent. As the last row in table 1 indicates, had this decline in the Gini been attained through a Lorenz-convex inequality reduction, it would have led to a halving of the incidence of poverty in just

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in 1985 prices. The World Bank later updated it to U.S.$1.08/day, in 1993 prices. To obtain the monthly poverty line in 1999 Brazilian reais, we computed

$$z = \text{U.S.\$}1.08 * 30 * (1/\text{PPP93}) * \text{Brazil's CPI} = 32.4 * 56.1243 * 38.30 = 22.11,$$

where the consumer price index (CPI) is measured in September 1999, with September 1993 as a base. Two of these numbers are measured with considerable error. First, 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. Second, Brazilian inflation rates were very high in 1993, so that the choice of base month in that year (that is, 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 would an average CPI for 1993, as reflected in the figure for 1998 in the World Bank's *World Development Indicators* (2002).

TABLE 1. Three Points on Brazil's MDG Isopoverty Curve[a]

Year	*Growth (β percent)*	*Inequality reduction (α percent)*	μ	*Headcount (percent)*	*Gini*
Actual distribution					
1990 (base year)	...	...	232.66	7.46	0.6119
1999	9.56	3.74	254.90	5.29	0.5889
Simulated distribution[b]					
A. 2015	0	3.40	232.66	3.71	0.5911
B. 2015	50	0	348.99	3.71	0.6119
C. 1997[c]	7.35	2.94	249.77	3.38	0.5939

Source: Authors' calculations, based on data from the 1990 and 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

a. $z =$ R$22.11 per person per month, in 1999 values, which corresponds to U.S.$1.00 per person per day.

b. The year listed for the simulation distributions indicates the year in which the MDG poverty target headcount would be achieved, starting in 1990.

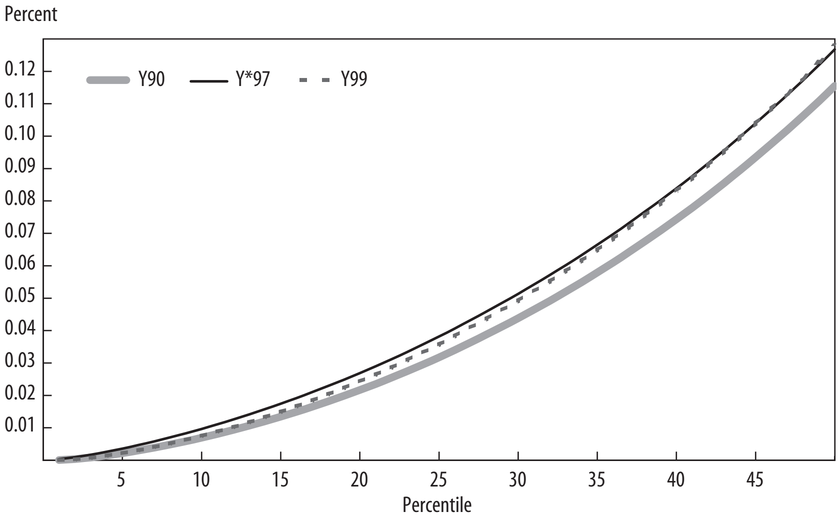
c. The third simulation is based on the historical average for the 1990–99 period, in which $\beta = 1.02$ percent and $\alpha = 0.43$ percent.

under seven years. With a cumulative growth in mean income of 7.35 percent and a Lorenz-convex fall in inequality of 2.94 percent (which corresponds to less than two points of the Gini), the Brazilian extreme-poverty headcount would have fallen to 3.38 percent by 1997.

Yet the actual observed incidence of extreme poverty in 1999 was 5.29 percent, despite the fact that accumulated growth in the PNAD mean income since 1990 was actually 9.56 percent, and the 1999 Gini coefficient was 3.74 percent 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 equation 3. This is clearly evident in figure 2, which we truncated at the median 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 $\alpha = 0.0294$. The dotted curve is the actual 1999 Lorenz curve. The actual reduction in inequality was not as beneficial to the bottom of the distribution as a Lorenz-convex transformation would have been.

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 shows the difference between the simulated distribution $F^*(\alpha = 0.0294,$

FIGURE 2. Actual and Simulated Truncated Lorenz Curves for Brazil

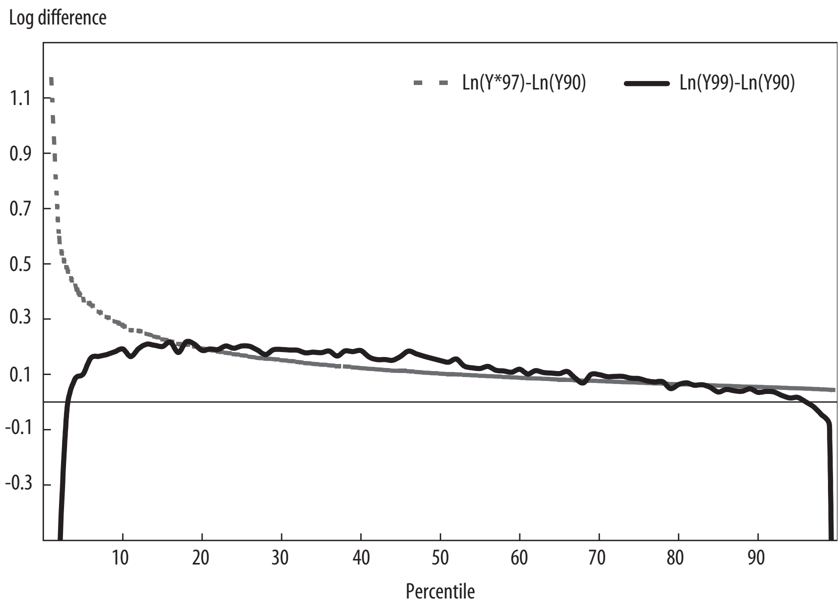


$\beta = 0.0735$) and the actual 1990 distribution, whereas the solid line plots the difference between the actual 1999 and the actual 1990 distributions. Although both distributions have lower Gini coefficients than the 1990 distribution, it is apparent that those distributions are obtained from the 1990 one through rather different processes. In particular, 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 equation 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 with household behavior in various realms, such as fertility or occupational decisions, that can affect the distribution of income, or with 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—

FIGURE 3. Actual and Simulated Log Income Differences per Percentile, 1990–99



inequality reduction could, in principle, be a very effective path toward the eradication of extreme poverty and the meeting of the MDG poverty-reduction target. 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 percent. While the average annual growth rate implied by this number (1.64 percent) 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. This refers only to the statistical trade-off between growth and inequality. Economically, it is quite possible that there may be additional trade-offs or, conversely, that some inequality reduction might facilitate growth.

ECLAC and UNDP undertake a similar exercise for eighteen countries in Latin America and the Caribbean, and find that only seven countries in the sample would meet their MDG poverty targets if their growth and inequality trends during the 1990s are replicated in 2000–15.[13] 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 never meet the MDG target under the assumption that their performances in the 1990s would extend indefinitely into the future.[15] In considering alternative scenarios, the report finds that isopoverty curves in the region are almost universally flat, implying that the poverty-reduction impact of a percentage-point reduction in the Gini coefficient (under the maintained assumption of Lorenz convexity) is equivalent to that of many percentage points in accumulated economic growth.

The 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.[16] 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 highly unequal country than in a more egalitarian one.[17] 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 beyond the statistical decomposition reported here, namely, that reducing inequality will probably not only reduce poverty directly now, but will also augment the future effects of economic growth on poverty.

13. ECLAC and UNDP (2002). The seven countries are 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 in the 1990s.

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

16. See, for instance, Bourguignon (2003).

17. See Ravallion (1997).

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 do not have high efficiency costs. In the particular case of Brazil, table 1 reveals that the growth rate required to halve extreme poverty from its 1990 level without any reduction in inequality would be 60 percent higher than the rate actually observed in the 1990s. Furthermore, in the absence of any economic growth, blanket untargeted redistribution would require a substantial additional fiscal effort of about 3.4 percent of gross domestic product (GDP). The clear implication is that whatever growth rate can be achieved in the next twelve years should be complemented by redistribution policies that are more directly targeted to the poor. They can thus contribute more effectively to poverty reduction, at a lower fiscal cost.

The simple simulation exercise reported in this section cannot take us much further than this. While it has been useful in deriving these general conclusions, the exercise has clear limitations. The Brazilian experience in 1990–99, 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, and changes in family composition. The next section presents an empirical model of household income determination that seeks to incorporate some of these key dimensions, in the hope that it can provide more specific policy guidance.

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 the different household members, and they thus depend on individual occupational decisions, on the members' human and physical assets, 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.[18]

—Block I: Household income aggregation. This identity simply defines a household's per capita income from the sum of labor incomes across occupations (indexed by j) and across household members (indexed by i):

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

All non-labor income accruing to the household is denoted by y_0, 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. The earnings equation is specified in the standard Mincerian manner:

$$Log\ y_{hi}^{j} = \mathbf{X}_i \boldsymbol{\beta}^j + \varepsilon_i. \tag{8}$$

We estimate four such equations separately: one for age group ten to fifteen years old, which is used only in the simulation of a specific policy (*Bolsa Escola*); another for the age group ten to eighteen years old; and two for those aged nineteen and older, including one for own-account workers (*conta-próprias*) and employers and another for wage-earning employees.[19] In all cases, workers are assigned to the sectors of their principal occupation. The vector **X**, as is customary, contains characteristics of both the worker and the job. In this case, **X** includes years of schooling (year dummies), age, age squared, age interacted with schooling, a gender dummy, race (white, nonwhite), formality status, and spatial variables (region of the country, urban/rural). The exact specification and results are reported in tables A1 and A2 in the appendix.

—Block III: Occupational structure. This block models the structure of occupations in the labor force by means of two similar discrete choice

18. 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 that operate through the conditional distribution of family sizes can be substantial. See also Ferreira and Leite (forthcoming).

19. Dummies are included to distinguish between *com carteira, sem carteira,* and public servants.

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. For those aged nineteen and older, the specification is

$$P_i^s = \frac{e^{Z_i\gamma_s}}{e^{Z_i\gamma_s} + \sum_{j \neq s} e^{Z_i\gamma_j}}, \tag{9}$$

where s and j are occupational categories. For those aged ten to eighteen, the model is written as

$$P_i^k = \frac{e^{(Z_i\gamma_k + Y_{-i}\alpha_k + w_i\beta_k)}}{\sum_j e^{(Z_i\gamma_j + Y_{-i}\alpha_j + w_i\beta_j)}}. \tag{10}$$

Table A3 contains the specification and results for those aged nineteen 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 ten to eighteen, 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.[20]

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 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 tractable the econometrics of joint estimation (with Block II). The model for ten- to eighteen-year-olds, on the other hand, is estimated as a structural model, with the predicted earnings from the earnings equation

20. We do not place much emphasis on the possible interpretations of equations 9 and 10 as reduced forms of utility-maximizing behavioral models. Instead, we interpret them as parametric approximations to the relevant conditional distributions—that is, 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.

reported in table A2 included as w_i on the right-hand side for all youngsters, as a measure of potential earnings.[21] 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. 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**:

$$\text{(11)} \qquad \text{OPM}\left(e \middle| a,r,g,s\right): P\left(e_i \middle| \mathbf{M}\right) = \Phi\left[c(e_i) - \mathbf{M}\boldsymbol{\delta}\right] - \Phi\left[c(e_{i-1}) - \mathbf{M}\boldsymbol{\delta}\right].$$

Unlike the choices underlying the occupational structure of the population, educational choices follow a specific ordering by years, and they 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 (Φ) evaluated at cut-off points estimated for levels e_i and e_{i-1}. The estimation results for equation 11, containing both the estimated values for $\boldsymbol{\delta}$ and the seventeen estimated cut-off points, are given in table A5.

Although it consists of only four basic equations, this model is rather more complicated than the one presented in the previous section. 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 that it 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 use equations 7 through 11 to simulate the effects of

21. 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 into account 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 right-hand side of the multinomial logit model. Selection issues in the sample for which the earnings equation is estimated are difficult to address. We follow Bourguignon, Fournier, and Gurgand (2002) in being skeptical of the Lee (1983) model for multivariate selection bias correction. We tried a bivariate Heckman correction procedure, but abandoned it because (a) it was inconsistent with a trivariate model of occupational choice, such as equation 10, and (b) the estimated coefficients of the Mills ratios had values that were difficult to interpret. This part of the model draws heavily on Bourguignon, Ferreira, and Leite (2002b), who discuss specification and estimation in greater detail.

three different policies on the Brazilian distribution of household incomes. Since the purpose of the exercise is forward-looking, we take the 1999 distribution as the base for the simulations.

Policy Scenario One is an increase in individual educational endowments.[22] To simulate this increase, we depart from the existing 1999 PNAD database to construct a 2015 counterfactual database. If we had panel data, or even many repeated cross-sections from which to construct pseudo-panels, we might try to analyze the educational, fertility, and occupational dynamics of different cohorts and predict how these cohorts might behave in 2015. Such longitudinal data are not available to us, however, and even if they were, we would still be faced with missing observations for the young in 2015.

Instead, we make some adjustments to the 1999 database. For individuals aged thirty-five or older, we predict education in the counterfactual (2015) database, 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 eighteen to thirty-four—that is, 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 percent a year) 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 seventeen or younger were left unchanged.[23]

22. We do not simulate the actual policies that might lead to these increases in educational attainment, such as additional expenditures on school inputs (such as teachers) or adoption of school vouchers. 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 that might generate such increases.

23. This assumption greatly simplifies the analysis, since it allows us to separate the educational simulation from the occupational choice problem of the young, which we address in the next two scenarios. It is probably unrealistic, however, to suppose that the educational preferences of the young would remain constant in a setting in which adults were more educated. The impact of this possible underestimation of schooling among the

These procedures generated counterfactual years of schooling for everyone in our simulated 2015 database. We then fed these counterfactual educational attainments through equations 8 and 9, generating a counterfactual occupational structure and a counterfactual earnings distribution for the population. Finally, we aggregated these through equation 7 to create 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 2 and figure 4, the results of this simulation are presented in two steps to highlight the composition of the effects. Table 2 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 and 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, and λ refers 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 (and of greater induced labor force participation, in the α, β, and λ simulation), but inequality behaves ambiguously.[24] 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 that some educational expansions can have when returns to schooling are

young on household incomes is ambiguous: on the one hand, those who acquired more education and dropped out of school would probably command higher wages; on the other, a number of children would be earning less (from child labor) because of more time spent studying.

24. Note that the returns to education are being kept constant here. This is clearly arbitrary, as changes in the relative supply of skills would generally 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. Owing to space constraints, we have chosen not to present such an analysis here, but see Ferreira and Leite (forthcoming) for an example.

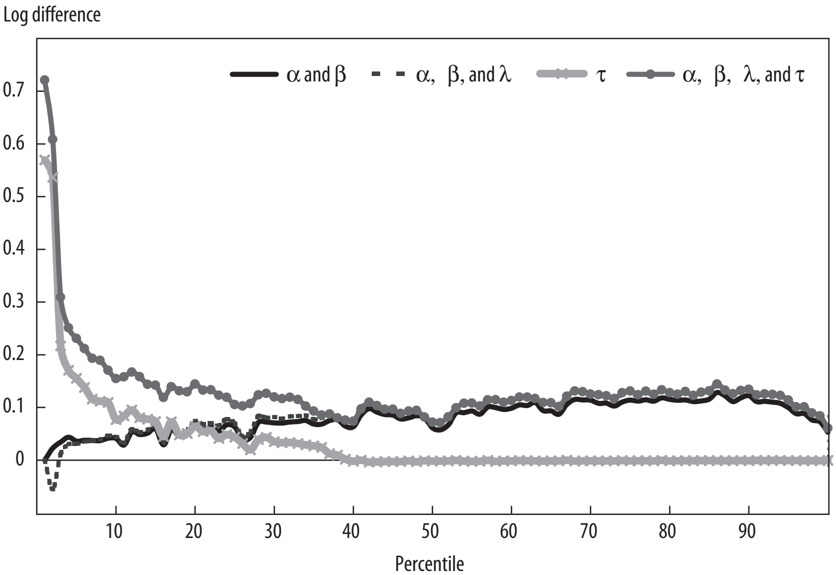
TABLE 2. Simulation Results for Three Policy Scenarios

			2015 simulations[a]				
Indicator	*1990*	*1999*	α *and* β	α, β, *and* λ	τ	t	α, β, λ, *and* t
Mean income	232.66	254.90	279.10	282.49	255.70	255.78	283.84
Poverty measures							
Poverty headcount—FGT(0) (percent)	7.46	5.29	4.98	5.02	4.14	3.87	3.68
Poverty gap—FGT(1) (percent)	2.97	2.50	2.40	2.45	1.91	1.78	1.73
FGT(2) (percent)	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 years)	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 years)	1.2695	1.3105	1.1460	1.1460	1.3106	1.3128	1.1414
Ratio of girls to boys in tertiary education (13 or more years)	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: Authors' calculations, based on data from the 1990 and 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

a. The simulations are as follows: α and β: policy scenario one, earnings effects only; α, β, and λ: policy scenario one, earnings and occupational effects; τ: policy scenario two; t: policy scenario three, transfers only; and α, β, λ, and t: policy scenario three, complete.

FIGURE 4. Log Differences Between Counterfactual 2015 and Actual 1999 Distribution



sufficiently convex.[25] In this case, an increase in unemployment and 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 with Ferreira and Paes de Barros's finding 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.[26]

As a result of these effects, the incidence of extreme poverty in Brazil in the simulated distribution falls only from 5.3 percent to around 5.0 percent—well short of the Millennium target of 3.73 percent. The Foster-Greer-Thorbecke (FGT) measures (1 and 2) fall even less, proportionately. This implies that educational expansions on the scale experienced in Brazil in the 1990s are unlikely to be sufficient, on their own, to carry the country through to meeting its first MDG target. Since education is often

25. For further discussion, see Almeida dos Reis and Paes de Barros (1991); Lam (1999); Bourguignon, Ferreira, and Lustig (1998).

26. Ferreira and Paes de Barros (1999).

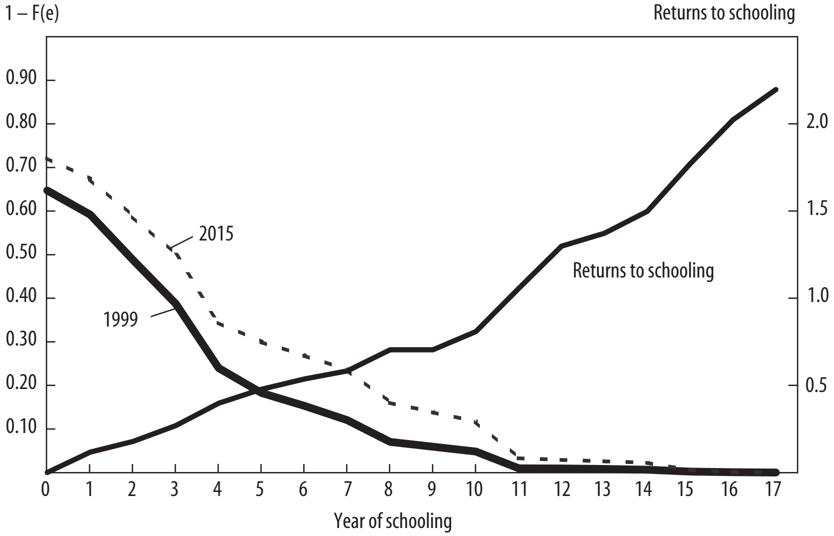
cited as something of a distributional panacea, this is not an entirely irrelevant finding for policymakers.

Why did the simulated expansion in education have 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 (one to four years), which the poorest people in society tend to have. Figure 5 plots (in the solid line) the complement to the cumulative distribution of years of schooling among the poor in Brazil in 1999—that is, the bottom 5.29 percent 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 workers. It shows that almost 80 percent of the poor (as defined by the international poverty line) in 1999 had four years of schooling or fewer. Even after the counterfactual expansion simulated under Policy Scenario One, nearly 70 percent of that group had four years of schooling or fewer. Marginal returns to additional schooling at those levels are very low. The results of the simulation in column 3 of table 2, in which 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 stemming from greater education.

There are a number of important caveats, of course. Returns are assumed to be constant, as is the constant term in equation 8, which might increase with economic growth arising from other sources. The impact of greater schooling among adults on the demand for education by their children is not taken into account.[27] Perhaps most important, substantial gains in per capita incomes can occur through reductions in fertility, which are

27. This impact is incorporated in Policy Scenario Three below, however. In any case, it wouldn't affect incomes in 2015, except through the labor earnings of children under the age of eighteen.

FIGURE 5. Actual and Counterfactual Distributions of Education (1–F(e)) among the 1999 Poor, with Returns to Schooling



not simulated here. In a separate study, for instance, we estimate the impact on household incomes of the reduction in the number of children in the household—both directly through reductions in the per capita denominator and indirectly through further increased female labor force participation.[28] In the simulation most closely comparable to this one, this factor accounted for just under a quarter of the overall educational impact.[29]

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 50 percent decline in poverty, owing to fertility effects even larger than those estimated in our earlier paper, this would still only

28. Ferreira and Leite (forthcoming).

29. Fertility effects could be simulated in that study because it 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 to take cohort effects into account, but the absence of panel or pseudo-panel data prevents us from undertaking cohort analyses in this exercise.

change the proportional decline in P_0 arising from this policy from 6 percent to 9 percent. All in all, it might be wise to pay heed to the finding that, under reasonable assumptions, educational expansions alone will not eradicate poverty in Brazil, however desirable they may be in themselves.

Table 2 also contains information about the other four targets considered in the paper. The poverty measures include the second indicator for the poverty and hunger goal, namely, the poverty gap. Like P_0, this measure falls very little as a result of the simulated Policy Scenario One. Net enrollment in primary education (toward the bottom of the table) shows considerable actual progress between 1990 (80 percent) and 1999 (93 percent). 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 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 return to this indicator in the other two simulations.

The next three rows in table 2 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). Between 1990 and 1999, women increased their enrollment advantage over men in both the secondary and tertiary levels, but they lost in the primary level. Given that repetition rates are higher for males in primary school, this might simply reflect a larger number of male grade-repeaters in primary school.[30] Alternatively, it might signal some deeper trend among young girls. An investigation of this issue is beyond the scope of this paper, but it deserves attention among those concerned with meeting the gender equality goal in Brazil. If gender *equality* is really the goal, the female advantage at the secondary and university levels is cause for concern. Are Brazilian men becoming an under-educated 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?

Finally, we use the ratio of women to men in wage employment to approximate indicator 11 (goal 3). It is only an approximation because we have not confined the analysis to the nonagricultural sectors. Once again, the historical gain in female employment in the 1990s is rather remarkable, as the ratio climbs from 56 percent to 71 percent. Looking forward

30. See Bourguignon, Ferreira, and Leite (2002b).

to 2015, the occupational response to the educational gains simulated under Policy Scenario One would further increase this ratio to just over 75 percent.

Since an educational expansion appears to be insufficient for meeting the MDG poverty-reduction goals, largely because it fails to raise incomes at the very bottom of the distribution, we now consider a 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 ignore the practical problems of identifying and reaching them—we simulate an existing transfer program that has received considerable attention and has recently been expanded as a federal program, namely, *Bolsa Escola*.[31] The simulation consists in 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 six and fifteen are in regular attendance at a public school, provided that the household's pre-transfer per capita income level is less than $Y^0 =$ R$90 per month.[32]

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 equation 10. These are given by equation 12, in which $j = 0$ denotes the occupational category of not attending school, $j = 1$ denotes attending school and working, and $j = 2$ denotes attending school only. Notation in that equation is exactly as in equation 10, and N is a part-time adjustment fac-

31. 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 that *starts* in 2015. We do not model the likely impacts of the earlier existence of such a policy (say, in 1999–2015) on additional schooling, or anything else. This is thus not an ex ante evaluation of *Bolsa Escola*. For that, please see Bourguignon, Ferreira, and Leite (2002b). Other studies describing early versions of the program and assessing their impacts include Rocha and Sabóia (1998); Sant'Ana and Moraes (1997); World Bank (2001).

32. 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).

tor for the potential wage of children who both work and study.[33] Since the standard estimation procedure for a multilogit model involves estimating the differences between parameter values (for example, $\alpha_1 - \alpha_0$ or $\beta_2 - \beta_0$), the introduction of incomes which are asymmetric across categories requires additional identification assumptions to enable the estimation of equation 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 assumption, the occupational choice model for the young, given by equations 10 and 12, was estimated both for ten- to fifteen-year-olds and for ten- to eighteen-year-olds (for reasons which will soon become apparent); the results are presented in table A4.

$$
\begin{aligned}
&U_i(0) = Z_i\gamma_0 + \alpha_0 Y_{-I} + \beta_0 w_i + v_{i0}, && \\
&U_i(1) = Z_i\gamma_1 + \alpha_1(Y_{-I} + T) + \beta_1 w_i + v_{i1} && \textit{if } Y_{-I} + Nw_i \leq Y^0, \\
&U_i(1) = Z_i\gamma_1 + \alpha_1 Y_{-I} + \beta_1 w_i + v_{i1} && \textit{if } Y_{-I} + Nw_i > Y^0, \\
&U_i(2) = Z_i\gamma_2 + \alpha_2(Y_{-I} + T) + \beta_2 w_i + v_{i2} && \textit{if } Y_{-I} \leq Y^0, \text{ and} \\
&U_i(2) = Z_i\gamma_2 + \alpha_2 Y_{-I} + \beta_2 w_i + v_{i2} && \textit{if } Y_{-I} > Y^0.
\end{aligned} \tag{12}
$$

One interesting benefit of estimating this structural model for the young is that it allows us to simulate the effect of *Bolsa Escola* transfers not only 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, and the *Programa de Asignación Familiar* (PRAF) in Honduras is to encourage human capital accumulation by rewarding school attendance.[34] We present the main results for the ten to fifteen age group in table 3.[35] 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).

33. See Bourguignon, Ferreira, and Leite (2002b).

34. 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); Schultz (2000).

35. For a more detailed discussion, see Bourguignon, Ferreira, and Leite (2002b).

TABLE 3. Simulated Effect of *Bolsa Escola* on Children's Schooling and Working Status[a]
Percent

Category	*Not studying*	*Working and studying*	*Studying*	*Total*
All households				
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	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: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).
a. All children aged ten to fifteen years.

The simulated impact of this transfer scheme is to reduce the number of children not enrolled in school by 36 percent among all households and by over 60 percent among poor households. About a third of these individuals would attend school but also keep working in the market. The remaining two-thirds would 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 2 (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 assumption, the increase in the mean is negligible, owing to the small size of the actual *Bolsa Escola* transfers.[36] Their targeting is effective, however, so 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 percent, which is 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 that suc-

36. 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.

cessfully 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 combine the previous two policies to simulate Policy Scenario Three, featuring 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 by applying the model in equations 7 through 12 to the original 1999 PNAD dataset, and then iterating upward 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 percent.[37] Remarkably, the value of the individual per-child transfer that 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 aged sixteen to eighteen are also eligible.[38]

The results for poverty and inequality are given in the last two columns of table 2 and by the α, β, λ, and τ line in figure 4. Column 6 in table 2 (labeled t) corresponds to the counterfactual distribution under the modified transfer scheme (that is, as in τ, but expanded to sixteen- to eighteen-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 percent—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 percent, just below

37. 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 equation 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 equation 9.

38. 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 sixteen- to eighteen-year-olds corresponds roughly to the extension of the benefit to secondary schools, which many commentators have suggested. See World Bank (2001); Camargo and Ferreira (2001).

the MDG target. The poverty gap ratio and FGT(2) also fall substantially from 1990, but by less than 50 percent.

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 stems 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, and τ line in figure 4. This line shows clearly that the largest proportional gains from Policy Scenario Three accrue exactly to the bottom 5 percent of the population—exactly the group that was overlooked by the educational expansion under Policy Scenario One.

Gains elsewhere in the distribution, particularly from the second quintile upward, 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. The transfers do, however, have a sizable impact on the schooling decisions of those children at which they are aimed. Table 4 is a counterfactual transition matrix analogous to table 3, but for ten- to eighteen-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 percent among all households and 65 percent among the poor.

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 percent of Brazilian GDP in 1999.

TABLE 4. Simulated Effect of *Bolsa Escola* on Children's Schooling and Working Status after Simulations[a]
Percent

Category	*Not studying*	*Working and studying*	*Studying*	*Total*
All households				
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	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: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

a. All children aged ten to fifteen years.

Conclusions

In this paper, we have sought to investigate whether microeconomic simulation techniques can shed any light on the kinds of policies that might help countries reach their Millennium Development Goals. Rather than trying to cover many countries superficially, we opted to test a richer set of approaches for a single country. We chose Brazil, with which we are most familiar. We started out with a simple statistical procedure based on different combinations of growth rates and inequality reductions that 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 it 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 (relative 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 the initial model is too aggregated for thinking about specific policies, be they for education, labor markets, redistribution schemes, or whatnot. 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 that generated the 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. We adopted an approach based on 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 database, 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 throughout the country. Policy Scenario Three was a combination of the previous two, with a limited expansion in the coverage of the transfer benefit.

Throughout, we have attempted to keep the limitations of the exercise and the strength of the underlying assumptions 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—especially the prices of skills in the labor market—will respond to the changes we simulate, or indeed to all the other myriad changes that we do not simulate and have no idea about. This abstraction from equilibrium responses is a general characteristic of simulations in the Oaxaca-Blinder family.[39] It is less problematic, however, when used in the context for which it was originally designed, namely, to decompose changes that have already happened and

39. Oaxaca (1973); Blinder (1973). For discussion, see DiNardo, Fortin, and Lemieux (1996); Bourguignon, Ferreira, and Leite (2002a).

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, these simulations generated some interesting findings. 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 they could take a very long time to be felt. If policymakers 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.

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 while a program like *Bolsa Escola* might not be sufficient in isolation and in its current format, it could be a very important tool in meeting the Millennium Development Goals if combined with a set of sustained policies aimed at expanding educational attainments. Given an educational expansion at the pace that was observed historically in Brazil during the 1990s, our Policy Scenario Three, which could be described as a *Bolsa Escola* extended to secondary school and without household ceilings, generates a counterfactual distribution in which the incidence of poverty is below the MDG target for the country. Finally, 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: 0.3 percent of GDP versus 3 percent of GDP.

These are not predictions 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. 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 that policymakers might want to focus on if they are interested in reducing extreme poverty in unequal middle-income countries.

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, 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.

Appendix

Equation 4 can be obtained as follows. We know that the Gini coefficient is given by

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

It follows from equation 1 that

$$\left| y_i^* - y_j^* \right| = (1+\beta)(1-\alpha)\left| y_i - y_j \right|.$$

Thus,

$$\sum\sum\left| y_i^* - y_j^* \right| = (1+\beta)(1-\alpha)\sum\sum\left| y_i - y_j \right|.$$

Dividing through by $2n^2(1 + \beta)\mu_y$, we get

$$(2n^2\mu_y^*)^{-1}\sum\sum\left| y_i^* - y_j^* \right| = \left(2n^2(1+\beta)\mu_y\right)^{-1}(1+\beta)(1-\alpha)\sum\sum\left| y_i - y_j \right|,$$

which yields equation 4.

TABLE A1. Mincerian Equation for Adults (over Eighteen Years Old)

	Self-employed and employer			*Employees: formal, informal, and public servants*		
Indicator	*Coefficient*	*Standard deviation*	*P > |z|*	*Coefficient*	*Standard deviation*	*P > |z|*
Years of schooling						
1 year	0.0805	0.0281	0.0040	–0.0086	0.0158	0.5840
2 years	0.1646	0.0245	0.0000	–0.0465	0.0131	0.0000
3 years	0.2202	0.0245	0.0000	–0.0332	0.0130	0.0100
4 years	0.3603	0.0251	0.0000	–0.0089	0.0128	0.4880
5 years	0.4145	0.0327	0.0000	0.0024	0.0156	0.8760
6 years	0.4470	0.0368	0.0000	0.0052	0.0177	0.7710
7 years	0.5210	0.0392	0.0000	–0.0214	0.0188	0.2540
8 years	0.5732	0.0393	0.0000	0.0416	0.0192	0.0300
9 years	0.5296	0.0548	0.0000	0.0302	0.0229	0.1860
10 years	0.6555	0.0505	0.0000	0.0495	0.0234	0.0350
11 years	0.8045	0.0482	0.0000	0.2230	0.0228	0.0000
12 years	0.9970	0.0890	0.0000	0.4566	0.0316	0.0000
13 years	1.0622	0.0756	0.0000	0.4579	0.0337	0.0000
14 years	1.0457	0.0796	0.0000	0.5351	0.0343	0.0000
15 years	1.3055	0.0697	0.0000	0.6911	0.0331	0.0000
16 years	1.4778	0.0758	0.0000	0.8992	0.0380	0.0000
17 years	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
Age squared	–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 nonmetropolitan	–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
Summary statistic						
R squared	0.52			0.59		
No. observations	39,071			81,918		

Source: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

TABLE A2. Earnings Equation for the Young

	Ten to fifteen years old[a]			*Ten to eighteen years old*[b]		
Indicator	*Coefficient*	*Standard deviation*	*P > |z|*	*Coefficient*	*Standard deviation*	*P > |z|*
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 squared	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
Area						
Urban nonmetropolitan	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
Region						
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
Summary statistic						
R squared	0.48			0.51		
No. observations	2,428			8,637		

a. Log of means earnings by cluster computed for children between the ages of ten and fifteen.
b. Log of means earnings by cluster computed for children between the ages of ten and eighteen.

TABLE A3. The Multinomial Logit Estimates for Participation Behavior and Occupational Choice for Adults (over Eighteen Years Old)[a]

	Self-employed		*Formal*		*Informal*		*Public servants*		*Employers*	
Indicator	*ME**	*P > |z|*	*ME**	*P > |z|*	*ME**	*P > |z|*	*ME**	*P > |z|*	*ME**	*P > |z|*
Years of schooling	...	0.000	...	0.000	...	0.121	...	0.000	...	0.000
Years of schooling squared	...	0.730	...	0.416	...	0.000	...	0.008	...	0.058
Age	...	0.000	...	0.000	...	0.000	...	0.000	...	0.000
Age squared	...	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
No. of household members										
Below 18 years old	0.004	0.000	−0.005	0.000	0.005	0.000	0.000	0.276	0.000	0.873
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
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 household	0.186	0.000	0.190	0.000	0.070	0.000	0.046	0.000	0.053	0.000
Second head of 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, is the head active?	0.002	0.178	−0.030	0.000	−0.006	0.000	−0.005	0.000	0.010	0.000
Area										
Urban nonmetropolitan	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
Summary statistic										
Pseudo R squared	0.1798									
No. observations	210,000									

Source: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

a. ME* is the marginal effect calculated from the estimated coefficients. The marginal effects for age and education are omitted owing to the interaction terms.

TABLE A4. The Multinomial Logit Estimates for Participation Behavior and Occupational Choice for the Young[a]

	Ten to fifteen years old				*Ten to eighteen years old*			
	Working and studying		*Studying*		*Working and studying*		*Studying*	
Indicator	*ME**	$P > \|z\|$	*ME**	$P > \|z\|$	*ME**	$P > \|z\|$	*ME**	$P > \|z\|$
Total household income	0.000	0.065	0.000	0.000	0.00	0.07	0.00	0.00
Children's earnings (what)	0.002	0.001	−0.004	0.000	0.00	0.02	0.00	0.00
Total people by household	0.009	0.000	−0.007	0.196	0.01	0.00	0.00	0.00
Age	. . .	0.000	. . .	0.000	. . .	0.00	. . .	0.00
Years of schooling	. . .	0.000	. . .	0.000	. . .	0.00	. . .	0.00
(Age-schooling) squared	. . .	0.001	. . .	0.091	. . .	0.00	. . .	0.01
White	−0.028	0.997	0.038	0.000	−0.02	0.55	0.02	0.00
Male	0.101	0.000	−0.087	0.036	0.08	0.00	−0.08	0.61
Max parent's education	−0.008	0.000	0.013	0.000	−0.01	0.00	0.01	0.00
Max parent's age	−0.001	0.403	0.001	0.000	0.00	0.00	0.00	0.00
Number of children (0 to 5 years old)	−0.001	0.000	−0.010	0.000	0.00	0.00	−0.02	0.00
Rank of child	0.014	0.219	−0.014	0.546	0.01	0.71	−0.02	0.00
Area								
Urban nonmetropolitan	0.031	0.015	−0.032	0.451	0.03	0.24	−0.04	0.00
Rural	0.212	0.000	−0.219	0.000	0.18	0.00	−0.22	0.00
Region								
North	0.093	0.000	−0.084	0.742	0.04	0.00	−0.03	0.00
Northeast	0.094	0.000	−0.076	0.006	0.06	0.00	−0.04	0.00
South	0.095	0.023	−0.117	0.000	0.07	0.74	−0.10	0.00
Center-West	0.069	0.002	−0.075	0.026	0.05	0.00	−0.06	0.01
Means of earnings by cluster	−0.002	0.000	0.004	0.000	0.00	0.22	0.00	0.00
Intercept	−0.729	0.000	1.216	0.000	−0.77	0.00	1.31	0.00
Summary statistic								
Pseudo *R* squared	0.2145				0.2557			
No. observations	43,418				65,507			

Source: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).

a. ME* is the marginal effect calculated from the estimated coefficients. The marginal effects for age and education are omitted owing to the interaction terms.

TABLE A5. Ordered Probit Model (Five Years Old or Older)

Indicator	*Coefficient*	*Standard deviation*	*P > |z|*
Age group			
5 to 10 years	−1.6811	0.0062	0.0000
11 to 18 years	−0.0218	0.0040	0.0000
Male	−0.0405	0.0041	0.0000
White	0.3851	0.0045	0.0000
Area			
Urban nonmetropolitan	−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: Authors' calculations, based on data from the 1999 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) of the Brazilian Institute for Geography and Statistics (IBGE).