DEPARTAMENTO DE ECONOMIA
PUC-RIO

TEXTO PARA DISCUSSÃO
N°. 456

EDUCATIONAL EXPANSION AND INCOME DISTRIBUTION

A Micro-Simulation for Ceará

FRANCISCO H.G. FERREIRA
PHILLIPPE GEORGE LEITE

MAIO 2002

Educational Expansion and Income Distribution

A Micro-Simulation for Ceará

Francisco H.G. Ferreira*
and Phillippe George Leite*

May 2002

Abstract

Does more education really mean less poverty and less inequality? How much less? What are the transmission mechanisms? This paper presents the results of a micro-simulation exercise for the Brazilian State of Ceará, which suggests that broad-based policies aimed at increasing educational attainment would have substantial impacts on poverty reduction, but muted effects on inequality. These results are highly dependent on assumptions about the behaviour of returns to education, both for the distribution of earnings and for the distribution of household income per capita. A large share of the poverty reducing effect of more education operates through greater incentives for labour force participation among the poor, and through reductions in fertility. Both of these effects function largely through decisions made by poor women.

Keywords: education, poverty, inequality

JEL classification: C15, D31, I31, J13, J22

---

*Pontifícia Universidade Católica, Rio de Janeiro. The authors are grateful, without implication, to Alex Araújo, François Bourguignon, Mike Walton and an anonymous referee for guidance and comments.

This study is linked to the theme of Growth and Poverty discussed at the WIDER Development Conference, 25-26 May 2001, Helsinki. UNU/WIDER gratefully acknowledges the financial support from the governments of Denmark, Finland and Norway to the 2000-2001 research programme.

1. Introduction

Ever since the introduction of the Human Capital model by Gary Becker and Jacob Mincer, economists have thought of earnings and income distributions as being fundamentally determined by the interaction between educational endowments and their market rates of return. In the specific case of Brazil, the seminal analysis of the country's income distribution by Carlos Langoni (1973) very much confirmed that view, and made education into the principal suspect in the search for culprits for the country's extreme levels of inequality. More recently, Barros et al. (2000) found that about 40 percent of overall inequality in the country's personal distribution of income could be ascribed to education.

In consequence, it has been widely assumed that if a government wishes to reduce poverty and inequality in a country like Brazil, the first policy it ought to adopt should be a general expansion of education.[1] Nevertheless, the historical evidence causes one to be less sanguine: in the United States, where 93 percent of the population reports nine or more years of schooling, income inequality has not been falling recently. The literature speaks of a changing structure of returns to education, whereby skill-biased technical progress (and in some contexts, possibly international trade) might be increasing demand for highly-educated workers, and offsetting (or more than offsetting) some of the equalizing results of expanding education. See Tinbergen (1975) for the classic reference, and Katz and Murphy (1992) for evidence on the US.

How might a substantial increase in the stock of education affect the income distribution in Brazil? In this paper, we simulate the impacts of a substantial expansion of education for the North-eastern Brazilian state of Ceará. This state was chosen precisely because of its very low educational endowments: mean years of schooling in the population (aged fifteen or older) was 4.5 in 1999. In the same year, forty-six percent of that population had fewer than four years of schooling. At the same time, Ceará's economy was not made up exclusively of subsistence agriculture. Forty-six percent of those employed worked in services or commerce, and another fourteen percent in industry. Under these conditions, it seemed to us that if an educational expansion would matter anywhere, it would matter here.[2]

The simulation is carried out at the household level, using the complete Ceará sub-sample of the IBGE's 1999 Pesquisa Nacional por Amostra de Domicílios (PNAD). In addition to simulating the effects on earnings of people having more education to trade in the labour market, under different sets of assumptions about the evolution of returns, we also consider the likely effects of additional education on labour force participation, occupational choice

[1] Although, to be fair, a number of studies have pointed out that the convexity of the relationship between returns and years of schooling implies that increases in education might actually lead to temporary increases in earnings inequality. See, for instance: Langoni (1973); Knight and Sabot (1983); Reis and Barros (1991); and Lam (1999).

[2] Additional demographic and occupational information for Ceará is contained in Table 1.

and fertility behaviour at the household level, and find that these matter a great deal to the overall picture.

As expected, the effects of a substantial educational expansion on poverty incidence are very substantial. The impact on inequality, however, is much more modest. Because of the changes in fertility and labour supply, we find that a very large part of the distributional changes arising from greater education depend on the behaviour of women. And location would matter marginally more, rather than less: while we do not simulate the effects on migration, our simulated poverty profile indicates that of the (fewer overall) poor people, (proportionately) more would be in rural areas.

The paper is structured as follows. Section 2 describes the reduced-form model of the income distribution which was estimated. Section 3 describes the specific simulation exercises which were undertaken. Section 4 highlights the main results, both for earnings and for household incomes, and suggests some interpretations. Section 5 concludes.

2. The model

In order to understand the impacts of different policies aimed at increasing educational endowments in the population of Ceará, we estimated a simple model of household income determination. The model builds on Ferreira and Paes de Barros (1999), which was in turn heavily influenced by Bourguignon et al. (1998) and Bourguignon et al. (2001).[3] This model—which is estimated on 1999 PNAD data for the state of Ceará—is recursive, and consists of five blocks, as follows:

Block I: household income aggregation

(1) $$Y_h = \sum_{i \in h} w_i L_i^w + \sum_{i \in h} p_i L_i^{se} + Y_{0h}$$

This equation simply adds up labour incomes for all household members, across the two sectors into which we assume the labour market is segmented: a wage sector (denoted by the superscript *w*) and a self-employment sector (denoted by the superscript *se*). *L* might have denoted hours, but given the nature of the information on labour supply in the PNAD data, it is actually a 0-1 participation dummy. Hence, w_i denotes the labour earnings of individual *i* in sector *w*, and ð$_i$ denotes the profits of individual *i* in the self-employment sector. The final term comprises all reported non-labour incomes accruing to the household.

Block II: earnings equation

(2) $$Log w_i = X_i \, b^w + e_i^w$$

(3) $$Log p_i = X_i \, b^{se} + e_i^{se}$$

[3] See also Juhn, Murphy and Pierce (1993).

Equations (2) and (3) are standard Mincerian earnings equations, estimated separately for the two labour market sectors. Both formal (‘com carteira’) and informal (‘sem carteira’) workers were treated as wage sector workers. Own account (‘conta própria’) workers were treated as self-employed. Employers were grouped alongside wage workers. 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*schooling, gender dummy, race (white, non-white), spatial (RM Fortaleza, other urban, rural) and sector (agriculture, services, industry). The estimation results for both equations are reported in Table 2.

Block III: occupational choice

(4) $$P_i^s = \frac{e^{Z_i g_s}}{e^{Z_i g_s} + \sum_{j \neq s} e^{Z_i g_j}} \quad \text{where } s, j = (0, w, se)$$

This block models the choice of occupation (into wage employment, self-employment or inactivity) by means of a discrete choice model—specifically, a multinomial logit—which estimates the probability of choice of each occupation as a function of a set of family and personal variables, namely: age, age squared, education, age*education, gender, race, spatial location, family composition, average age in the family (excluding the individual), average education in the family (excluding the individual), dummy if head of household, dummy if the head is inactive, dummy if spouse.

Note that this occupational choice model is written in reduced form, as 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.[4] Inactivity was used as the reference occupational category. The estimated coefficients of the model and the marginal effects they imply are reported in Table 3.

Block IV: demographic choices

(5) $$\text{ML}\ (n_c \mid a, e, r, s, n_a)$$

This block uses a similar model to (4), which we now write in short form—ML stands for multinomial logit. This estimates the probability of choosing a certain number of children (0, 1, 2, 3, 4, 5+), as a function of the woman’s age, education, race, spatial location, and the number of adults in the household. The variable used for the number of children in the estimation refers to the number of sons and daughters of the mother, which were alive and living in the household at the time of the survey. Five or more children was used as the

[4] See Bourguignon et al. (1998) for a discussion.

reference category. The estimated coefficients of the model and the marginal effects they imply are reported in Table 4.

Block V: educational choice

$$OPM(e \mid a, r, g, s): P(e_i|M) = \Phi[c(e_i) - Md] - \Phi[c(e_{i-1}) - Md] \tag{6}$$

This block models an individual's choice of final education 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 Blocks III and IV, educational choice follows a specific ordering by years, and is 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 (Ö) evaluated at cut-off points estimated for levels e_i and e_{i-1}. The estimation results for (6), containing both the estimated values for ä and the seventeen estimated cut-off points, are given in Table 5.

Note that we do not place any emphasis on the possible interpretations of equations (2)-(6) 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 form of the relevant joint multivariate distributions. See Bourguignon, Ferreira and Leite (2002) for a more detailed statistical discussion of this kind of counterfactual analysis.

3. Simulating Educational Expansions

Educational expansions are not, of course, all alike. One would expect to obtain very different distributional results, say, from two policies, one of which aimed to triple the number of university graduates in the state, and another which aimed to halve the number of illiterate people. How exactly the histogram of the distribution of years of schooling changes matters as much as how the overall mean evolves. In addition—and as alluded to above—the same expansion in education will have different impacts depending on how demand for skills changes in the labour market. To allow for both of these concerns to the extent possible, six simulations were undertaken, corresponding to two different 'policy choices'[5], with different aims in terms of the distribution of education; and to three sets of assumptions about returns in the labour market.

The first 'policy' was one of indiscriminate expansion. We simulate this as a rise in the mean of the distribution of years of schooling, from 4.5 (the observed level in 1999), to seven years. Of course, one might raise the mean of a distribution in very different ways. Since we observe how educational attainment is distributed jointly with age, gender, race

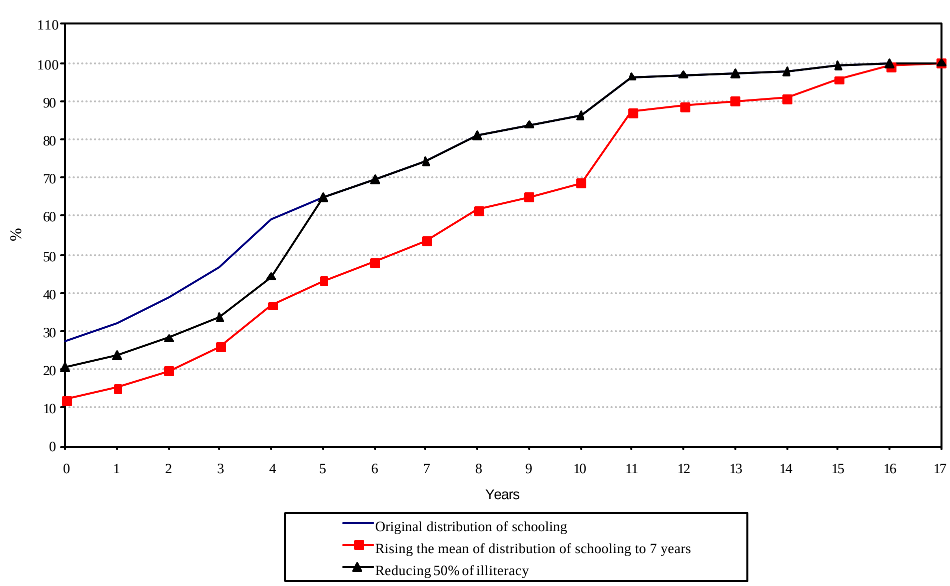
[5] The term "policy" is used loosely here. The two scenarios are actually defined in terms of outcomes, rather than of policy decisions about inputs. We do not discuss which variables within the control of policy makers might be changed - or how they might be changed - in order to persuade individuals to alter their educational choices so as to generate these desired outcomes. Such a discussion lies beyond the scope of this paper.

and spatial location in the state, through our estimation of equation (6) above, we simulate the expansion in a manner consistent with that pattern. Specifically, we implemented a computer algorithm whereby the vector of cut-off points $c(e_i)$ in the ordered probit model was translated leftwards by a constant vector **è** > 0; such that $c'(e_i) = c(e_i)$ - è. For each individual i, with observed schooling level e_i and other characteristics M_i, the model had been estimated so that $c(e_{i-1}) < M_i$ ä + $æ_i < c(e_i)$.[6]

In the simulation, we simply re-compute the schooling level of individual i such that: $c'(e_{i-1}) < M_i$ ä + $æ_i < c'(e_i)$. c' < c for all e_i has the desired effect of increasing the frequency of educational choices at levels higher than those actually observed. The program iterated on successively higher values of è, until the mean of the simulated distribution of years of schooling converged to seven. By shifting the distribution in this manner, without altering the estimated values for ä, we preserve the observed conditionality of educational choices on other characteristics.

The second 'policy' we investigate is a focused effort to reduce illiteracy. We change the distribution of education by moving *fifty percent* of those individuals between the ages of 15 and 40, and with four years of schooling or less, to five years (exactly), by selecting those with the highest probability of moving from amongst all possible candidates. As before, this is implemented by translating the estimated cut-off points in the ordered probit model. This time, only the five first cut-off points are translated leftwards (by a constant value ê), such that the ensuing simulated cumulative distribution of years of schooling for 15-40 year-olds (F') is, when evaluated at e = 4, equal to half of its observed value: F'(e=4) = 0.5*F(e=4). The original cumulative distribution function of years of schooling in Ceará in 1999 (for the population aged fifteen or older), as well as the two simulated distributions, are shown in Figure 1.

Figure 1: CDFs of years of schooling in Ceará: Actual and Simulated



[6] The variable æ is an individual residual, the distribution of which is, by construction, a truncated normal N(0,1).

The results of each of these two educational ‘policies’ are simulated under three alternative returns scenarios, namely:

1. â$_{99}$: Keep all âs values as estimated for the 1999 regressions.
2. â convex: with respect to category 13+ (omitted), lower â for 0-4 years of schooling by 20 percent; for 5-8 by 15 percent; and for 9-12 by 10 percent. To ensure the growth neutrality of these changes, the constant term á was adjusted to maintain mean earnings (for that category of worker and for the original observed X matrix) constant at its observed 1999 level.
3. â concave: with respect to category 13+ (omitted), raise â for 0-4 years of schooling by 30 percent, for 5-8 by 20 percent and 9-12 by 10 percent. The constant term was adjusted in a manner analogous to that in point (2) above.

So the six simulations are given by the following schematic 2x3 matrix:

Simulation	â (1999)	â concave	â convex
Policy One			
Policy Two			

4. Results

The main simulation results are presented in Tables 6 and 7. Table 6 reports mean earnings and five different inequality measures, for each of the six simulations, for the distribution of labour earnings among earners with positive labour incomes.[7] Table 7 presents the corresponding results for the distribution of household incomes by individuals and includes, in addition to the same inequality measures as Table 6, three poverty measures—P(á), for á = 0, 1 e 2.[8] The poverty line was set at R$68.00, which is the line officially suggested by the Planning Institute of the State Government of Ceará, (IPLANCE). In each of the above tables, the measures presented in the row ‘Ceará’ *of the panel â$_{99}$* are those for the actual observed distribution in 1999. The measures presented in the row ‘Ceará’ in the other two panels arise from imposing the simulated structure of returns (more concave or more convex) on the existing 1999 population—with its actual distributions of education and other characteristics.

For each of the six combinations of educational outcomes and returns, poverty and inequality statistics are presented for three different simulations, denoted by sets of Greek letters. The first of these, denoted by á, â and ó^2 , consists of running the required simulation—of the first or of the second "policy"—and feeding the simulated distribution of education through the earnings models (2) and (3), either unadjusted (â$_{99}$), or adjusted (â$_{convex}$ or â$_{concave}$). Original residuals are used, and this generates a counterfactual (i.e. simulated) distribution of earnings, under the required assumption about returns, which corresponds to the new distribution of education. This educational distribution was, in turn,

[7] The inequality measures used were the Gini coefficient, the Generalized Entropy indices for parameter values 0, 1 and 2; and the variance of logarithms. Simulated populations are also included, to show the simulated changes in participation.

[8] These are the poverty measures defined in Foster et al. (1984). Simulated populations included in Table 7 reflect counterfactual changes in fertility behaviour.

obtained from simulating an increase in schooling according to the ordered probit model in (6). In this simulation, each individual preserves his or her initial (1999) occupation and family composition. All that may change is the amount of education they sell in the labour market and, for the convex and concave scenarios, the rate at which they do so. We call the result of this simulation the "pure market" effect.

We know, however, that labour force participation and occupational choice are also heavily dependent on education. It is natural to suppose that changes in schooling endowments such as the ones being simulated here for Ceará are likely to have some impact on who is working, and on where they are working. This is investigated by allowing the simulated distributions of education to feed through the occupational choice model (4), the parameters of which are denoted by ã's. The second row in each panel thus summarizes the inequality and poverty statistics pertaining to the distributions which are simulated when, in addition to the educational endowment being transacted and to the structure of returns, we allow for occupational choices and labour force participation to change.[9] These counterfactual distributions, denoted by "ã, á, â and ó^{2}", incorporate two effects: the "pure market" effect and the "occupational" effect.

Finally, the third row allows for family size—driven by the number of children 'demanded' by each family—to change also. This is achieved by allowing the simulated distributions of education to feed through the demographic choice model (5), the parameters of which are denoted by øs. This has two second-round effects on household incomes: first, as the number of children in a family changes, the income per capita denominator changes, and it is recalculated accordingly. Second, the number of children in the household is, as it must be, an independent variable in the occupational choice multi-logit model (4). In this row of simulations results the ãs and øs interact, since changes in occupational choice reflect not only chances in the educational levels of the individuals (and of others in their families) but also changes in the number of under-16s living in the household. The resulting counterfactual distributions, denoted by "ø, ã, á, â and ó^{2}", incorporate three effects: "pure market", "occupational" and "demographic".

While the aggregated information presented in Tables 6 and 7 tell the basic story, additional insights can be gained from looking at the entire distribution. Figures 2-13 plot the differences in the logarithms of mean incomes for each percentile, between the simulated distribution and the real 1999 distribution: figures 2-7 refer to the earnings distribution, while figures 8-13 correspond to the distributions of household per capita income. Each distribution is ranked by its own distributed variable. The lines for á, â and ó^{2} correspond to the "pure market" effect: simulations where each earner had his or her level of education changed to a level drawn for it in the new distribution of education, as described above. To simulate the concave and convex cases, the âs were changed as appropriate.

As indicated above, in these simulations, people are selling more education on the labour market, but are still working in the same occupation as before, and have exactly the same family composition. The lines that include a ã simulate the additional effect of those

[9] In order to simulate the earnings of new entrants into the labour force, each needs to be allocated to a sector of activity (agriculture, industry or services). We did not model those choices explicitly, and thus simply allocate each entrant randomly, using the observed 1999 sector frequencies as probabilities.

changes in years of schooling on people's labour force participation and/or occupational choices. And those that include a ø as well, also incorporate the effect of those extra years of schooling on the number of children each family is likely to have, and any subsequent additional impact which that may have on occupational choice.

4.1 Effects on earnings

The overall simulated effect of Policy One - which consisted of raising mean years of schooling in Ceará from 4.5 to seven, in a manner which was consistent with individual propensities to acquire education - turns out to be both (i) income-increasing and (ii) generally equalizing. This overall effect is, however, rather sensitive to the assumptions about the behaviour of the returns structure. It also reflects the aggregation of pure market effects, occupational effects and demographic effects, which are heterogeneous and interesting in their own rights.

The rise in mean earnings can be seen from a comparison of the simulated means under Policy One, with the 'Ceará' mean, in Table 6. In fact, mean incomes are higher than the actual 1999 mean (R$286.70) for all simulations, in all three returns scenarios. They are highest, in fact, for the pure market effect. As labour market participation and occupational choice effects are incorporated, mean earnings fall under all three returns scenarios. This is largely due to the fact that most entrants have earnings below the mean, thus contributing to its reduction.

Despite these similarities in aggregate terms, the differences in the distribution of income gains across the returns scenarios are quite marked. This is particularly evident from inspection of Figures 2-4: whereas the educational expansion would result in large gains (between 30% and 50%) for the very poor if returns to the low skilled rose (see Figure 3), the increases would stay in the 0-30% range if returns became more convex (Figure 4).

Naturally, the effects on inequality also vary with respect to returns. When compared to the observed earnings Gini (of 0.590) in 1999, the pure market effects of an educational expansion would lower inequality if returns became flatter (Figure 3), but raise it in the other two cases. Another way of seeing this is that the pure market effect when the effect of changes in the structure of returns is netted out[10] - is generally *inequality-increasing*. This is the case for the Gini, E(0), E(1) and the variance of logarithms in all cases.[11] This confirms the results found by Langoni (1973), Knight and Sabot (1983) and Reis and Barros (1991), that educational expansions in the presence of convex returns may lead to increases, rather than declines, in inequality.

This picture changes, however, when we allow for the impact of the educational expansion on participation and demographic behaviour. The Gini for the counterfactual earnings distributions that incorporate the occupational choice (ã), and demographic effects (ø) of greater education is almost three points below that for the pure market effect in all three returns scenarios. In Figures 2-4 it can be clearly seen that the occupational and

[10] To see this, compare inequality measures in each á, â, $ó^2$ row with those in "Ceará" row in the same panel.

[11] E(2), which is driven largely by the upper tail of the distribution, goes the other way.

demographic effects[12] make a difference at the tails of the distribution, raising incomes for the poor and lowering them somewhat for the rich. As a result of the participation effects arising from more education and from fewer children, the labour force expanded by approximately 150,000 people each time the educational effect on occupational choice was taken into account. It turns out that the composition of the net entrants into the labour force is such that it lowers overall earnings inequality.

Figures 14 and 15, which present the frequency of entrants (net of exits) per percentile of the distribution of household incomes, shows that the progressiveness of higher participation draws predominantly on the self-employment sector. The profile of net entrance into the wage sector is somewhat more regressive. Many of those entering into the higher ranges of the wage sector do, however, come themselves from self-employment.[13] Higher levels of education tend, in this sense, to upgrade the occupational profile, as non-participants enter (largely) into self-employment, and many previously in that sector move into wage jobs.

The effects of Policy Two - which consisted of a targeted effort at reducing illiteracy, by halving the proportion of persons with four years of schooling or less - were rather different. The rows for simulations under Policy Two in Table 6 reveal much smaller increases in mean earnings for the pure market effect, and actual declines for the complete simulation. Inequality reductions, however, were considerably larger for Policy Two than for Policy One. This is particularly true if returns stay constant or become more concave: if the â vector remained as in 1999, the overall effect of Policy Two on the Gini would be a fall of between three and four points. If the returns became more concave, the Gini would fall seven points, to approximately 0.52. This is a fairly serious change, and leads to an inequality level which is not high, by Brazilian standards.

Figures 6 and 7 confirm that, for this particular policy, the configuration of returns is crucial: if returns to the unskilled rise, then the impact of having a little more education on the welfare of those who are at the bottom of the distribution will be positive and substantial. Most people in the bottom quintile of the distribution would have between 10 percent and 40 percent higher earnings. If, on the other hand, Policy Two were combined with a decline in the returns to lower levels of schooling, as in Figure 7, then educational gains would just about exactly offset the impoverishing effect of the change in returns.

4.2 Effects on household incomes

When compared to the changes in earnings distributions, the simulations for household income distributions reveal both similarities and differences. Qualitatively, the market, occupational and demographic effects of both "policies" on the income distributions are

---

[12] Figures 2-7 reveal that the demographic effects are muted for earnings distributions. The line for the all-effects simulation lies very close to the line for joint occupation and pure market effect simulation. This is because the only effect of reductions in fertility rates on earnings is through induced changes in participation and occupational choice. For households, the demographic effect also includes changes in the denominator of household income per capita and, as Figures 8-13 show, this makes them considerably larger.

[13] Recall that the simulations which include the ã parameters change the pattern of occupational structure across these two sectors, as well as changes in participation status.

rather similar to those observed for earnings. Policy One - raising the mean education level to seven years - increases mean incomes for all return scenarios, and does so by more than Policy Two in all cases. See Table 7. Policy Two only raises mean income in the pure market effect simulation, and leaves it basically unchanged after all effects are taken into account. In terms of inequality reduction, the rank of the two "policies" is reversed - as in the case of the earnings distributions. Policy Two leads to lower inequality than Policy One in every simulation, according to most (though not all) inequality measures.

Perhaps the most marked difference between the per capita income results and those for earnings are that occupational choice and demographic effects seem to matter more for the former than for the latter. One explanation is that the demographic effect is considered fully in the household simulations: the reduction in the denominator of household per capita incomes, as a result of lower fertility, is explicitly taken into account here. Another part of the explanation comes from the fact that the individuals who are considered alone in the earnings distribution, are not organized into families in a random manner. Hence, many of the entrants into the labour force turn out to reside in poor families and their new labour supply becomes highly equalizing in the distribution of household incomes. It is also chiefly among the poor that the effect of more schooling on fertility—to reduce the number of children in the household, thus raising per capita incomes—is particularly pronounced.

It is thus that Figures 8-10 have the curves with ã indicating larger income increases for the poor than the pure market effect simulation, and those with both ã and ø higher still. The sharp downward turn in these log-income difference curves for the top 5% of the population also contribute to an equalizing effect. This is confirmed by inspecting the inequality measures in Table 7: from an observed 1999 level of 0.613, the Gini could fall by almost three points under Policy One (and around 5.5 points under Policy Two) if returns became more concave.

Assumptions about the return structure continue to matter a great deal. If returns convexified—which we saw was a powerful unequalizing force on the distribution of earnings—the Gini would rise by 1.5 points under Policy One, once all effects have been taken into account. If returns were identical to those of 1999, the Gini would stay roughly constant. The different returns scenarios are clearly still very important, generating only slightly less variation in outcomes in terms of household income inequality than was the case for earnings. This is because households pool resources, and provide insurance to individual members: even if assortative mating is very pronounced in Brazil[14] (and we suspect, in Ceará), education levels still do differ across individuals in the same household, so that changes in returns hurt or benefit the pooled family less than it might hurt or benefit each member.

The combination of rising mean incomes and falling inequality should spell good news for poverty reduction, as a result of the educational expansion simulated in Policy One. Indeed, with respect to the state's poverty line of R$68.00 per capita per month, we observe declines in poverty headcount (or incidence) as large as 12.9 percentage points (or about a quarter), when returns become more concave. Poverty simulation results also

[14] The simple correlation coefficient between the years of schooling reported by household heads and their spouses in the 1999 PNAD (for all of Brazil) is 0.73, which compares with 0.63 in the US, for instance.

depend on the structure of returns, but somewhat less than inequality. If returns became more convex, Policy One would still lower P(0) by 9.8 percentage points, from the 1999 level of 51.8 percent, to 42 percent. Each of these results takes into account all simulated effects of the greater endowment of education and, in particular, its labour supply, occupational and demographic impacts. Their importance is once again highlighted by the fact that, in their absence, the poverty reduction effect of the educational expansion would be considerably smaller. Specifically, with constant returns, the fall excluding these effects would be of approximately seven percentage points, rather than eleven.

Policy Two represents, as we have seen in the earnings simulation, a different choice along the mean-inequality trade-off. Targeted at the lower tail of the education distribution, this policy leads to smaller (or no) increases in mean income, for each stage of the simulation, and for each assumption about returns. On the other hand, it also leads to greater reductions in inequality than Policy One for most (although not all) inequality measures, in all simulations in Table 7. In terms of the poverty results presented on that same table, the gains in inequality reduction from choosing Policy Two over Policy One fail to compensate for the smaller increases in absolute incomes that would ensue. In fact, poverty would be higher under Policy Two than under Policy One, for all return scenarios, all simulation stages and, somewhat surprising, for all three poverty indices considered.

More important than the absolute number of poor people is an understanding of who they are and where they live. Table 8 shows the effects of the "policies" considered above on the composition of the poor, rather than just on their level. The profile is constructed by location, gender of the household head and schooling of the household head. The first column gives the composition of the total (actual) population in 1999, broken down by those categories. The next two columns give poverty incidence in the subgroup (P(0)), and the share of the poor population which belongs to the subgroup (composition). The next six columns present counterfactual analogues to columns 2 and 3 for Policy One, under each alternative returns scenario. The last six columns do the same for Policy Two.

The poverty profile is much more robust across "policies" and returns scenarios than absolute poverty levels were. Composition of the poor by gender is basically unchanged across all of the simulations. In contrast, some differences can be discerned across policies, for the educational and geographical dimensions of the profile. But these are not large. The profile by years of schooling hardly changes at all between the observed 1999 profile and that simulated for Policy Two. Under Policy One, however, it becomes slightly steeper, with a greater proportion of the poor having no education, and a smaller proportion among the most educated. One should always remember, of course, that this refers only to the composition of the poor. The P(0) columns served to remind us that under these simulated policies, the overall numbers of the poor would be smaller.

Finally, although neither "policy" was designed in a spatially sensitive manner, Policy One appears to marginally reinforce the prevalence of rural poverty. This is largely because living in rural areas is currently associated with having lower educational attainment and, as a result, the ordered probit that assigns the distribution of extra years of schooling among individuals, allocates them more often to urban residents, ceteris paribus. Hence, whereas 45 percent of Ceará’s poor today live in rural areas, this might rise to just over fifty percent, if special care is not taken to encourage faster enrollment and good school supply in rural areas.[15]

5. Conclusions

As with most uses of econometric estimates to make out-of-sample predictions, the results of our microsimulation exercise should be treated with considerable circumspection. Probably even more than most. Household data is measured with substantial error. Educational data based on years of schooling, in particular, is famously a very poor measure for quality-adjusted human capital stocks. Our models of fertility and occupational choices are acceptable only as very reduced forms. And their parameters, as indeed all others, may very well change over time or as a response to policy reforms.

Having said all this, the following four conclusions appear to receive broad support from our analysis, and might be of some use to those concerned with the impact of educational expansions on the distribution of economic welfare in developing societies.

First, a broad-based expansion of enrollment and a reduction in evasion rates which raised average endowments of education (from 4.5 to seven years, in this case), would be very likely to make a substantial contribution to poverty reduction. Just how substantial seems to depend somewhat on how the structure of returns to education evolves. In this exercise, the simulated decline in P(0) ranged from some ten points (or 20%) when returns became more convex, to thirteen points (or about a quarter) when they became more concave. These policies would not, however, have the same impact on inequality. While the simulated educational expansion (under Policy One) would be moderately equalizing if returns became more concave, it would be neutral if returns did not change. And inequality would actually rise if returns became more convex at the same time as the expansion took place.

Second, a combination of policies which succeeded in expanding education in a more targeted way (by halving the share of 15-40 year-olds with 0-4 years of schooling, in this case) would contribute to making educational expansions more progressive. As noted above, in the presence of convex returns to schooling, educational expansions can be inequality-increasing. At best, an increase in the mean of schooling may have reasonably small reductions in inequality, as just reported for Policy One. A more targeted effort, focusing on reducing illiteracy and keeping in school those most likely to leave, while not as likely to lead to large income gains across the population, can play an important role in reducing income inequality. Naturally, such a targeted exercise should not be seen as a substitute, but rather as a complement, to a broader expansion of educational opportunities across the board.

Third, as has already been noted, all results depend heavily on what happens to returns to education, which are determined by the interaction between the relative supply of and demand for different skills. In this paper, we did not model the demand side of the labour

[15] Notice that the more targeted Policy Two does not seem to increase the rural composition of poverty in the same way. This is presumably because, being targeted to the least educated, it is effectively (if unintentionally) targeted to rural areas.

market at all. While we provided estimates for three possible scenarios, effectively considering a range for the variation in returns, there is no guarantee that actual changes must remain within that range. Given that gains in labour earnings to the poor are very sensitive to these changes, a stagnation of demand for unskilled labour should cause particular cause for concern. The interaction between supply and demand for skills in the labour market has been an area of growing interest for researchers.[16] These advances hold out the promise of improvements in our understanding of the interaction between educational outcomes and the distribution of income.

Fourth, if our analysis shed any light at all on the impact of an educational expansion on the distribution of income in Ceará, it was on the crucial role played by household dynamics in the process. We saw that the State appears to have something of a 'reserve army', awaiting conditions to enter paid or self-employment. As in other places where educational levels rose rapidly, this is to a large extent composed of women.[17] As they acquire education and enter the labour force, their fertility behaviour also changes, reducing the number of children in the family.

In income terms, each of these tendencies is positive for the families to which they belong. In fact, the participation and demographic changes arising from educational expansion account for a substantial share of the overall poverty reduction impact. Figures 8, 9 and 10 illustrate the great importance of these gender-sensitive effects on the overall welfare of poor families. In the labour market, however, a large inflow of women into relatively underprivileged segments may generate downward wage pressure or enhance job competition. The extent to which Ceará will be able to capitalize on a more educated labour force depends, in large measure, on how effectively it ensures a level playing field for its women.

In closing, it should be noted that a number of important choices, or dimensions of household and worker behaviour, remained outside the scope of our analysis. Key amongst these is the possible decision to migrate. Greater endowments of education might affect the flows of migrants within the state—say, from rural areas to metropolitan Fortaleza—or outwards from the state. These decisions are likely to be determined by the relative conditions of labour demand, and thus wages, in these areas, and in other states. This falls outside the scope of this simple model, but this does not make it any less important a concern for policy-makers.

16 Katz and Murphy (1992) and Juhn, Murphy and Pierce (1993) have suggested methods to estimate changes in the demand for different labour skill categories, based on sectoral changes in the composition of economic activity. Robillard et al. (2001) combine a computable general equilibrium model and micro-simulations to consider demand and supply changes in the labour market simultaneously and in general equilibrium.

17 See Bourguignon et al. (2001) on the key role played by changes in female participation in the Taiwanese development process.

References

Barros, R., Henriques, R., Mendonça, R. (2000) 'Pelo Fim das Décadas Perdidas: Educação e Desenvolvimento Sustentado no Brasil', in Henriques, R. (ed.) *Desigualdade e Pobreza no Brasil*, IPEA: Rio de Janeiro.

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

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

Bourguignon, F., Fournier. M., Gurgand, M. (2001) 'Fast Development with a Stable Income Distribution: Taiwan, 1979-1994', *Review of Income and Wealth*, **47** (2): 139-164.

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.

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

Henriques, R. (ed.) (2000) *Desigualdade e Pobreza no Brasil*, IPEA: Rio de Janeiro.

Langoni, C. (1973) *Distribuição de Renda e Desenvolvimento Econômico do Brasil*, Expresso e cultura: Rio de Janeiro.

Juhn, C., Murphy, K., Pierce, B. (1993) 'Wage Inequality and the Rise in Returns to Skill', *Journal of Political Economy*, **101** (3): 410-42

Katz, L., Murphy, K. (1992) 'Changes in the Wage Structure 1963-87: Supply and Demand Factors', *Quarterly Journal of Economics*, **107**: 35-78

Knight, F. and R. Sabot (1983): "Educational Expansion and the Kuznets Effect", *American Economic Review*, **73** (5), pp.1132-1136.

Lam, D. (1999): "Generating Extreme Inequality: Schooling, Earnings, and Intergenerational Transmission of Human Capital in South Africa and Brazil", University of Michigan, Population Studies Center, Research Report No. 99-439.

Reis, J. A., Barros, R. (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**: 117-43.

Robillard, A.-S., Bourguignon, F. and Robinson, S. (2001): "Crisis and Income Distribution: A Micro-Macro Model for Indonesia", mimeo, IFPRI, Washington, DC.

Tinbergen, J. (1975) *Income Differences: Recent Research'* North Holland Publishing: Oxford.

Table 1: Some Basic Statistics: Ceará, 1999

	Number of People	%
Population	6.979.143	
Area		
Metropolitan area	2.710.515	38,8
Urban non metropolitan	2.024.916	29,0
Rural non metropolitan	2.243.712	32,1
Education		
0	2.659.053	38,1
1 to 3	1.556.349	22,3
4	711.873	10,2
5	369.895	5,3
6	251.249	3,6
7	244.270	3,5
8	314.061	4,5
9 to 12	725.831	10,4
13 or more	146.562	2,1
Age		
0 to 15	2.554.366	36,6
16 to 19	621.144	8,9
20 to 24	593.227	8,5
25 to 29	509.477	7,3
30 to 34	488.540	7,0
35 to 39	439.686	6,3
40 to 44	355.936	5,1
45 to 49	300.103	4,3
50 to 54	258.228	3,7
55 to 59	237.291	3,4
60 to 64	202.395	2,9
65 and +	418.749	6,0
Gender		
Male	3.397.997	48,7
Female	3.581.146	51,3
Employed	3.213.202	93,7
Unemployed	215.424	6,3
Employed with positive income	2.376.618	-
Occupational status		
Wage sector	2.189.963	68,2
Self-employment sector	1.023.239	31,8
Sector of activity		
Agriculture	1.277.371	39,8
Industry	459.853	14,3
Services/commerce/other	1.475.978	46,0

Source: PNAD/IBGE 1999

Table 2: The Estimated Earnings Equations for Ceará 1999

	Earnings				Self-employed			
	R^2	coef	std	p-value	R^2	coef	std	p-value
	0,60				0,49			
Intercept		3,74468	0,13845	0,000		4,08840	0,36039	0,000
Education								
0		-0,64439	0,12721	0,000		-2,06720	0,34671	0,000
1 to 3		-0,64560	0,12758	0,000		-1,80917	0,34941	0,000
4		-0,58645	0,13453	0,000		-1,60963	0,36074	0,000
5		-0,61238	0,15325	0,000		-1,69725	0,40503	0,000
6		-0,37910	0,17295	0,028		-1,22831	0,45498	0,007
7		-0,58931	0,15252	0,000		-1,15326	0,44791	0,010
8		-0,30600	0,14263	0,032		-1,03733	0,39813	0,009
9 to 12		-0,44252	0,12347	0,000		-0,92092	0,36618	0,012
13 or more		-	-	-		-	-	-
Age		0,09121	0,00502	0,000		0,08813	0,01042	0,000
Age^2		-0,00066	0,00005	0,000		-0,00082	0,00008	0,000
Age * education								
0		-0,03277	0,00318	0,000		-0,00619	0,00795	0,436
1 to 3		-0,03043	0,00333	0,000		-0,00924	0,00808	0,253
4		-0,02815	0,00347	0,000		-0,00888	0,00835	0,288
5		-0,02538	0,00446	0,000		-0,00127	0,01013	0,900
6		-0,03499	0,00509	0,000		-0,01196	0,01166	0,305
7		-0,02586	0,00441	0,000		-0,01572	0,01154	0,173
8		-0,03079	0,00392	0,000		-0,01169	0,00943	0,215
9 to 12		-0,01643	0,00328	0,000		-0,00409	0,00876	0,640
13 or more		-	-	-		-	-	-
Race - White		0,10523	0,01721	0,000		0,14007	0,03522	0,000
Gender - Male		0,46123	0,01666	0,000		0,94254	0,03865	0,000
Metropolitan area		0,44765	0,03182	0,000		0,30244	0,05620	0,000
Urban non metropolitan		0,11562	0,03477	0,001		0,10798	0,05443	0,047
Rural non metropolitan		0,00000	0,00000	0,000		0,00000	0,00000	0,000
Sector of activity								
Agriculture		-0,17467	0,03842	0,000		-0,67360	0,05685	0,000
Industry		0,07316	0,01912	0,000		-0,10259	0,05074	0,043
Services/commerce/other		0,00000	0,00000	0,000		0,00000	0,00000	0,000

Source: PNAD/IBGE 1999

Table 3: The Estimated Occupational Choice Multilogit Model

	Wage sector			Self-employment/employer sector		
	coef	p-value	dP_w/dx	coef	p-value	dP_{se}/dx
Gender - Male	1,120	0,000	0,083	1,928	0,000	0,231
Age	0,181	0,000	*	0,263	0,000	*
Age2	-0,002	0,000	*	-0,003	0,000	*
Education						
1 to 3	0,794	0,000	*	0,776	0,004	*
4	0,512	0,030	*	0,954	0,001	*
5	0,840	0,011	*	0,828	0,064	*
6	-0,356	0,329	*	0,340	0,526	*
7	0,268	0,408	*	1,007	0,043	*
8	0,444	0,094	*	-0,331	0,433	*
9 to 12	0,985	0,000	*	0,956	0,002	*
13 or more	2,536	0,000	*	2,541	0,000	*
Age * education						
1 to 3	-0,015	0,002	*	-0,012	0,033	*
4	-0,008	0,139	*	-0,015	0,020	*
5	-0,019	0,070	*	-0,006	0,625	*
6	0,017	0,142	*	0,004	0,813	*
7	0,005	0,596	*	-0,017	0,234	*
8	-0,004	0,553	*	0,015	0,161	*
9 to 12	-0,008	0,134	*	-0,014	0,049	*
13 or more	-0,023	0,017	*	-0,044	0,003	*
Metropolitan area	-1,361	0,000	-0,147	-1,882	0,000	-0,199
Urban non metropolitan	-1,055	0,000	-0,151	-1,086	0,000	-0,088
Average endowments of age	-0,004	0,123	0,000	-0,004	0,113	0,000
Education among adults in his or her household						
0	-0,517	0,005	-0,123	-0,039	0,864	0,044
1 to 3	-0,340	0,077	-0,108	0,244	0,298	0,077
4	-0,444	0,036	-0,126	0,176	0,493	0,075
5	-0,252	0,287	-0,072	0,105	0,729	0,044
6	-0,422	0,099	-0,122	0,182	0,566	0,074
7	-0,338	0,168	-0,081	-0,014	0,965	0,031
8	-0,495	0,025	-0,137	0,154	0,591	0,076
9 to 12	-0,763	0,000	-0,192	0,047	0,843	0,084
13 or more	-1,011	0,000	-0,231	-0,174	0,626	0,069
Numbers of adults in the household	0,008	0,669	0,005	-0,029	0,250	-0,006
Numbers of children in the household	0,021	0,217	-0,002	0,073	0,000	0,011
The individual is the head in the household	0,606	0,000	0,018	1,319	0,000	0,174
The individual is not the head in the household	0,143	0,168	0,067	-0,326	0,035	-0,072
The individual is the spouse in the household	0,136	0,110	-0,017	0,510	0,000	0,077
If not the head, is the head active?	-0,101	0,420	-0,032	0,073	0,705	0,023
Intercept	-2,214	0,000	-	-6,103	0,000	-

Source: PNAD 1999/IBGE

Note: * Marginal effects were not computed for the interaction variables.

Table 4: The Estimated Demographic Choice Multilogit Model

	Ceará (1999) Number of children													
	0			1			2			3			4	
	coef	p-value	dP_0/dx	coef	p-value	dP_1/dx	coef	p-value	dP_2/dx	coef	p-value	dP_3/dx	coef	p-value
Race - White	0,281	0,115	0,023	0,271	0,127	0,017	0,245	0,170	0,009	0,152	0,420	-0,006	-0,357	0,122
Numbers of adults in the household	-0,669	0,000	-0,078	-0,408	0,000	0,001	-0,281	0,000	0,028	-0,288	0,000	0,015	-0,201	0,003
Age	0,093	0,000	0,013	0,045	0,000	-0,001	0,028	0,000	-0,004	0,021	0,000	-0,003	0,014	0,028
Education														
1 to 3	0,163	0,392	-0,011	0,219	0,247	0,005	0,292	0,130	0,020	0,158	0,450	-0,005	0,239	0,309
4	0,889	0,000	0,031	0,683	0,006	-0,026	0,981	0,000	0,042	0,915	0,001	0,016	0,403	0,190
5	1,689	0,001	0,020	1,602	0,001	-0,005	1,972	0,000	0,075	1,778	0,000	0,020	1,178	0,027
6	1,886	0,001	0,043	1,886	0,001	0,036	2,034	0,000	0,063	1,752	0,002	0,001	0,829	0,204
7	24,163	0,000	0,426	24,105	0,000	0,341	24,334	0,000	0,342	23,832	0,000	0,136	21,949	.
8	2,411	0,000	0,106	2,212	0,000	0,039	2,320	0,000	0,056	1,811	0,001	-0,031	0,968	0,117
9 to 12	2,834	0,000	0,164	2,490	0,000	0,051	2,453	0,000	0,036	1,830	0,000	-0,057	1,007	0,072
13 or more	23,886	0,000	0,508	23,503	0,000	0,327	23,500	0,000	0,281	23,075	0,000	0,110	21,236	.
Metropolitan area	0,761	0,000	0,101	0,469	0,008	0,011	0,291	0,105	-0,029	0,106	0,572	-0,040	0,040	0,852
Urban non metropolitan	0,301	0,146	0,076	-0,011	0,957	-0,015	-0,037	0,857	-0,018	-0,204	0,351	-0,031	-0,118	0,638
Intercept	-1,777	0,000	-	-0,032	0,905	-	0,164	0,521	-	0,258	0,359	-	-0,066	0,841

Source: PNAD 1999/IBGE

Note: 5+ is the reference category

Table 5: The Estimated Ordered Probit Model for Education

	Ceará (1999)		
	coef	std	p-value
Age	-0,025	0,000	0,000
Gender - Male	-0,206	0,001	0,000
Race - White	0,426	0,001	0,000
Metropolitan area	1,085	0,001	0,000
Urban non metropolitan	0,597	0,001	0,000
Cut-off points			
1	-1,002	0,002	
2	-0,840	0,002	
3	-0,611	0,002	
4	-0,360	0,002	
5	0,027	0,001	
6	0,231	0,001	
7	0,385	0,001	
8	0,555	0,001	
9	0,821	0,001	
10	0,939	0,001	
11	1,059	0,001	
12	1,811	0,002	
13	1,890	0,002	
14	1,956	0,002	
15	2,011	0,002	
16	2,435	0,002	
17	3,099	0,004	

Source: PNAD 1999/IBGE

Table 6: Counterfactual Distribuitions of Individual Earnings: Descriptive Statistics

	Mean Earnings	Inequality					Population
		Gini	E(0)	E(1)	E(2)	V(log)	
$\boldsymbol{\beta}_{99}$							
Ceará	286.7	0.590	0.650	0.784	2.223	1.116	2,275,534
First Policy - Raising mean schooling to 7 years							
a. be s^2	401.6	0.616	0.722	0.796	1.923	1.306	2.275.534
g. a. be s^2	382.5	0.592	0.650	0.719	1.663	1.169	2.425.989
v. g. a. be s^2	379.9	0.588	0.642	0.710	1.646	1.159	2.422.323
Second Policy - Reducing illiteracy by 50%							
a. be s^2	292.8	0.584	0.634	0.763	2.132	1.093	2.275.534
g. a. be s^2	270.4	0.552	0.555	0.652	1.659	0.975	2.297.828
v. g. a. be s^2	270.8	0.551	0.554	0.653	1.685	0.971	2.295.578
$\boldsymbol{\beta}_{concave}$							
Ceará	286.7	0.556	0.569	0.683	1.821	0.998	2,275,534
First Policy - Raising mean schooling to 7 years							
a. be s^2	374.8	0.584	0.638	0.709	1.623	1.164	2.275.534
g. a. be s^2	356.6	0.556	0.563	0.620	1.291	1.025	2.425.989
v. g. a. be s^2	358.1	0.557	0.564	0.621	1.292	1.024	2.421.087
Second Policy - Reducing illiteracy by 50%							
a. be s^2	290.3	0.553	0.562	0.673	1.778	0.989	2.275.534
g. a. be s^2	266.9	0.515	0.478	0.547	1.214	0.865	2.297.828
v. g. a. be s^2	268.5	0.518	0.483	0.555	1.238	0.867	2.295.065
$\boldsymbol{\beta}_{convex}$							
Ceará	286.7	0.616	0.717	0.864	2.593	1.218	2,275,534
First Policy - Raising mean schooling to 7 years							
a. be s^2	419.9	0.639	0.791	0.866	2.207	1.428	2.275.534
g. a. be s^2	399.7	0.616	0.719	0.794	1.987	1.290	2.425.989
v. g. a. be s^2	396.6	0.613	0.710	0.783	1.963	1.279	2.422.323
Second Policy - Reducing illiteracy by 50%							
a. be s^2	293.6	0.607	0.693	0.836	2.470	1.183	2.275.534
g. a. be s^2	271.5	0.578	0.617	0.734	2.062	1.068	2.297.828
v. g. a. be s^2	271.9	0.578	0.616	0.736	2.107	1.064	2.295.578

Source: PNAD/IBGE 1999

Table 7: Counterfactual Distributions of Household per Capita Incomes: Poverty and Inequality

	Mean per capita Income	Inequality					Population	Poverty: Poverty line equal R$68.00		
		Gini	E(0)	E(1)	E(2)	V(log)		P(0)	P(1)	P(2)
β_{99}										
Ceará	135.3	0.613	0.733	0.846	2.421	1.378	6,978,331	51.8	24.4	15.3
First Policy - Raising mean schooling to 7 years										
$\alpha, \beta, \varepsilon, \sigma^2$	172.4	0.630	0.786	0.846	2.093	1.534	6,978,331	45.1	21.1	13.2
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	174.6	0.618	0.751	0.794	1.856	1.490	6,978,331	43.4	19.9	12.3
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	181.6	0.610	0.728	0.765	1.739	1.461	6,669,583	40.9	18.3	11.1
Second Policy - Reducing illiteracy by 50%										
$\alpha, \beta, \varepsilon, \sigma^2$	137.2	0.607	0.716	0.827	2.349	1.353	6,978,331	50.1	23.4	14.5
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	130.9	0.587	0.665	0.760	2.059	1.283	6,978,331	50.1	22.9	14.0
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	133.0	0.582	0.651	0.747	2.010	1.252	6,868,846	48.9	21.8	13.2
$\beta_{concave}$										
Ceará	135.3	0.587	0.664	0.766	2.106	1.275	6,978,330	48.6	21.8	13.3
First Policy - Raising mean schooling to 7 years										
$\alpha, \beta, \varepsilon, \sigma^2$	163.7	0.606	0.716	0.776	1.866	1.414	6,978,330	43.4	19.7	12.0
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	165.7	0.592	0.680	0.720	1.618	1.374	6,978,330	41.4	18.5	11.1
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	173.3	0.585	0.657	0.697	1.522	1.321	6,682,688	38.9	16.7	9.9
Second Policy - Reducing illiteracy by 50%										
$\alpha, \beta, \varepsilon, \sigma^2$	136.4	0.583	0.656	0.756	2.069	1.263	6,978,330	47.4	21.3	12.9
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	129.7	0.561	0.601	0.681	1.750	1.186	6,978,330	47.1	20.7	12.4
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	132.4	0.558	0.592	0.678	1.752	1.155	6,860,223	45.9	19.8	11.7
β_{convex}										
Ceará	135.3	0.631	0.785	0.905	2.683	1.459	6,978,331	54.2	26.3	16.8
First Policy - Raising mean schooling to 7 years										
$\alpha, \beta, \varepsilon, \sigma^2$	178.3	0.648	0.841	0.901	2.300	1.629	6,978,331	46.1	22.3	14.1
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	180.6	0.636	0.807	0.851	2.069	1.587	6,978,331	44.5	21.1	13.3
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	187.6	0.628	0.782	0.820	1.936	1.556	6,669,583	42.0	19.5	12.0
Second Policy - Reducing illiteracy by 50%										
$\alpha, \beta, \varepsilon, \sigma^2$	137.5	0.624	0.763	0.882	2.593	1.424	6,978,331	52.3	25.0	15.8
$\gamma, \alpha, \beta, \varepsilon, \sigma^2$	131.2	0.606	0.713	0.818	2.314	1.357	6,978,331	52.3	24.6	15.4
$\omega, \gamma, \alpha, \beta, \varepsilon, \sigma^2$	133.4	0.601	0.698	0.806	2.262	1.323	6,868,846	51.1	23.5	14.5

Source: PNAD/IBGE 1999

Table 8: Actual and Simulated Poverty Profiles for Ceará

				Raising mean schooling to 7 years						Reducing illiteracy by 50%					
		Observed values		β_{99}		β_{convex}		$\beta_{concave}$		β_{99}		β_{convex}		$\beta_{concave}$	
	Frequency	P(0)	Composition	P(0)	Composition	P(0)	Composition	P(0)	Composition	P(0)	Composition	P(0)	Composition	P(0)	Composition
Ceará		51.79		40.88		42.01		38.85		48.89		51.12		45.90	
Metropolitan	38.80	35.61	26.68	21.13	20.06	21.71	20.05	21.32	21.29	32.57	25.85	34.15	25.92	31.32	26.48
Urban	29.00	49.86	27.92	39.60	28.10	41.16	28.41	36.94	27.57	46.23	27.42	48.52	27.53	42.84	27.07
Rural	32.10	73.08	45.30	65.90	51.75	67.31	51.43	62.12	51.32	71.30	46.81	74.26	46.63	66.55	46.55
Men	48.70	52.84	49.69	42.09	50.15	43.18	50.05	39.97	50.10	50.02	49.82	52.32	49.85	46.79	49.65
Women	51.30	50.80	50.31	39.72	49.85	40.90	49.95	37.80	49.91	47.82	50.18	49.97	50.15	45.05	50.35
Years of schooling															
0	38.10	63.54	46.74	53.53	49.89	55.44	50.28	50.54	49.56	60.32	47.01	63.13	47.05	56.11	46.58
1	6.50	68.23	8.56	57.37	9.12	58.97	9.12	55.34	9.26	63.68	8.47	66.78	8.49	61.29	8.68
2	8.00	62.86	9.71	51.71	10.12	53.60	10.21	49.16	10.12	59.02	9.66	61.26	9.59	54.62	9.52
3	7.80	58.72	8.84	47.34	9.03	48.12	8.93	44.74	8.98	54.68	8.72	57.66	8.80	51.33	8.72
4	10.20	50.11	9.87	38.31	9.56	38.66	9.39	37.10	9.74	46.86	9.78	49.33	9.84	44.57	9.90
5	5.30	49.20	5.03	33.87	4.39	34.46	4.35	32.54	4.44	47.37	5.14	50.35	5.22	44.59	5.15
6	3.60	45.64	3.17	26.86	2.37	27.05	2.32	26.28	2.44	43.94	3.24	45.35	3.19	41.96	3.29
7	3.50	39.70	2.68	23.61	2.02	23.79	1.98	23.61	2.13	38.96	2.79	40.78	2.79	36.15	2.76
8	4.50	26.19	2.28	15.38	1.69	15.57	1.67	14.63	1.69	25.07	2.31	25.35	2.23	23.82	2.34
9	1.80	27.60	0.96	21.07	0.93	22.05	0.94	19.92	0.92	26.52	0.98	27.27	0.96	26.49	1.04
10	1.60	22.02	0.68	18.36	0.72	17.91	0.68	17.01	0.70	22.31	0.73	22.22	0.70	21.93	0.76
11	6.50	10.31	1.29	4.08	0.65	4.08	0.63	3.32	0.55	9.91	1.32	9.79	1.25	9.69	1.37
12	0.40	1.53	0.01	0.00	0.00	0.00	0.00	0.00	0.00	2.30	0.02	2.30	0.02	1.53	0.01
13	0.30	2.05	0.01	1.03	0.01	1.03	0.01	1.03	0.01	2.05	0.01	2.05	0.01	2.05	0.01
14	0.20	1.44	0.01	1.44	0.01	1.44	0.01	1.46	0.01	1.44	0.01	5.05	0.02	1.44	0.01
15	1.00	0.29	0.01	0.29	0.01	0.29	0.01	0.29	0.01	0.29	0.01	0.29	0.01	0.29	0.01
16	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: PNAD/IBGE 1999

Figure 2: EARNINGS - Raising mean schooling to 7 years, β_{99}

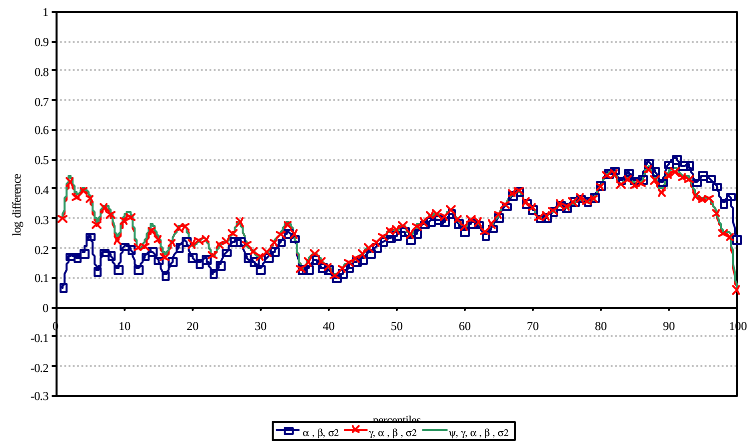


Figure 3: EARNINGS - Raising mean schooling to 7 years, $\beta_{concave}$

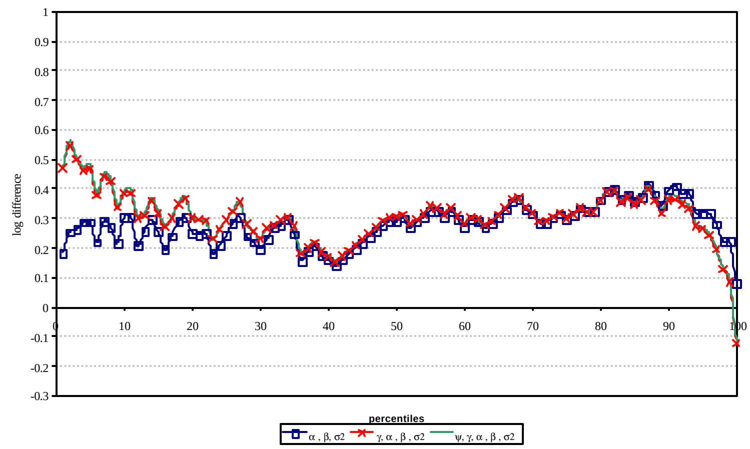


Figure 4: EARNINGS - Raising mean schooling to 7 years, β_{convex}

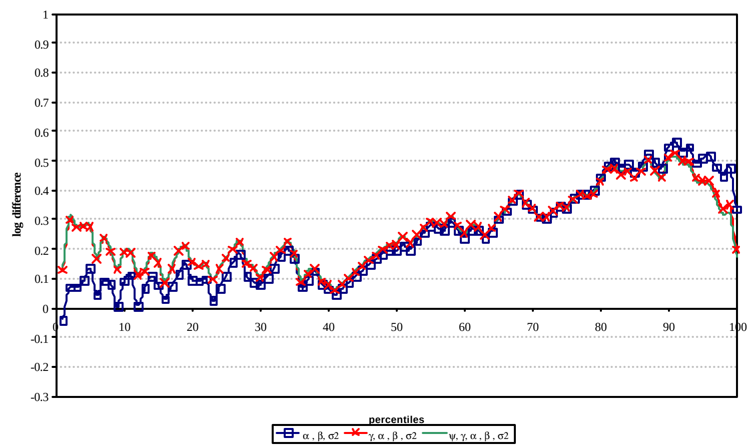


Figure 5: EARNINGS - Reducing illiteracy by 50%, β_{99}

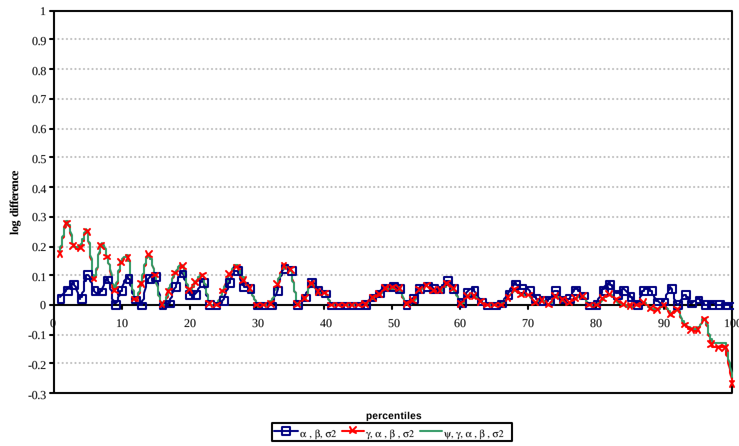


Figure 6: EARNINGS - Reducing illiteracy by 50%, $\beta_{concave}$

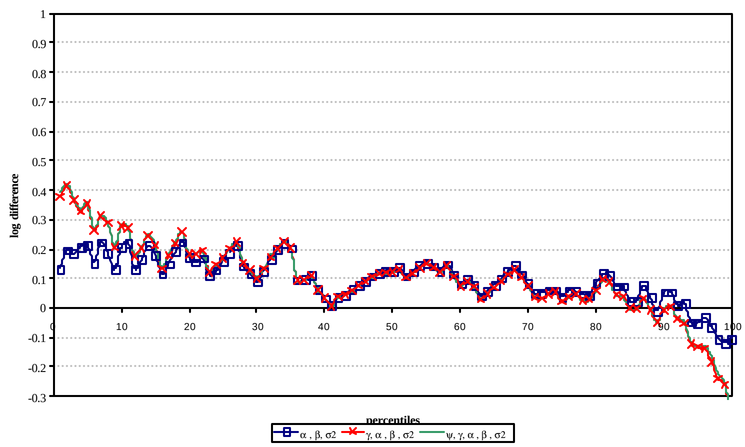


Figure 7: EARNINGS - Reducing illiteracy by 50%, β_{convex}

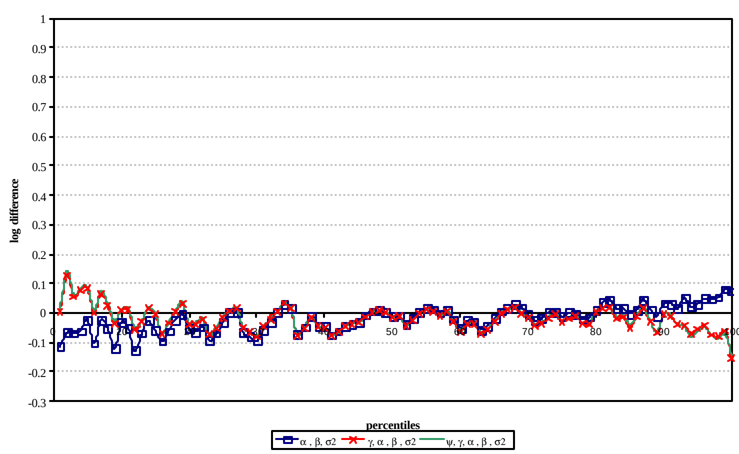


Figure 8: HOUSEHOLDS -Raising mean schooling to 7 years, β^{99}

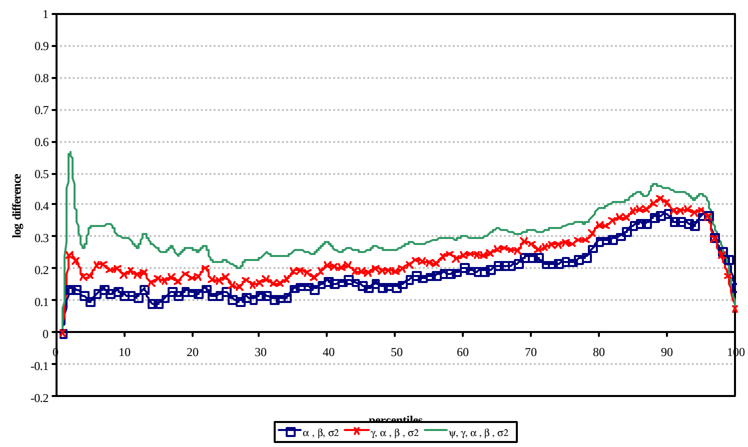


Figure 9: HOUSEHOLDS -Raising mean schooling to 7 years, $\beta^{concave}$

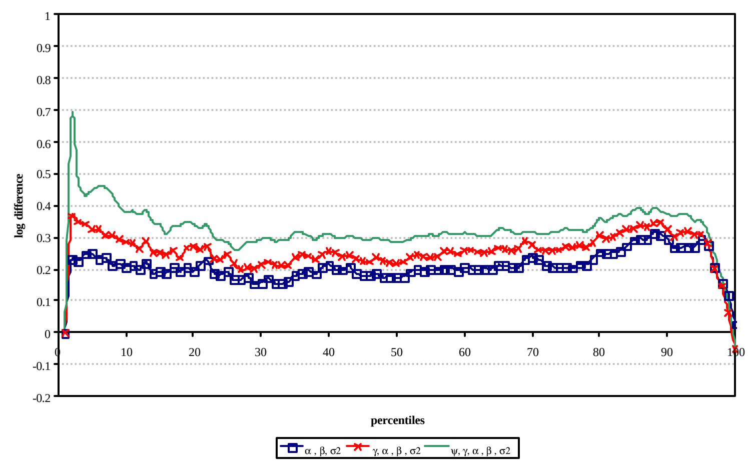


Figure 10: HOUSEHOLDS -Raising the mean schooling to 7 years β^{convex}

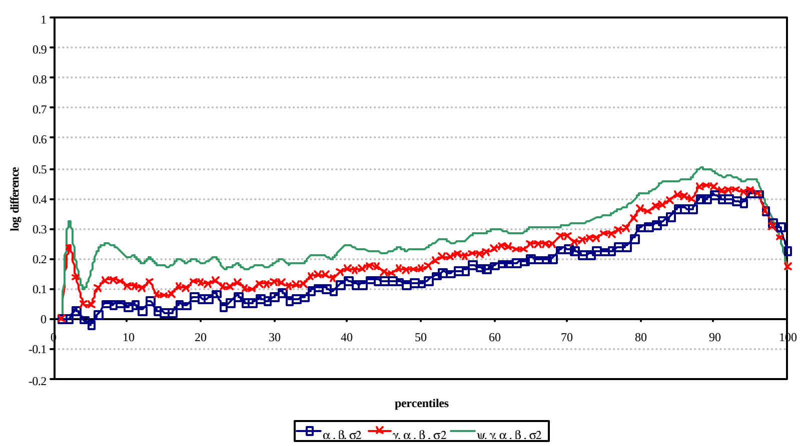


Figure 11: HOUSEHOLDS - Reducing illiteracy by 50%, β_{99}

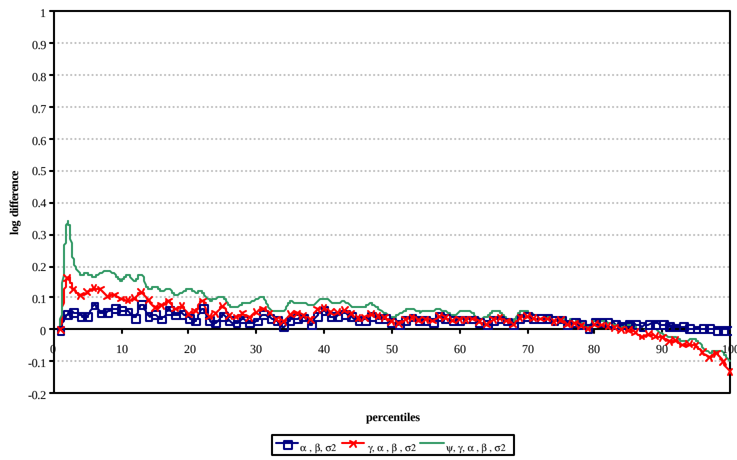


Figure 12: HOUSEHOLDS - Reducing illiteracy by 50%, $\beta_{concave}$

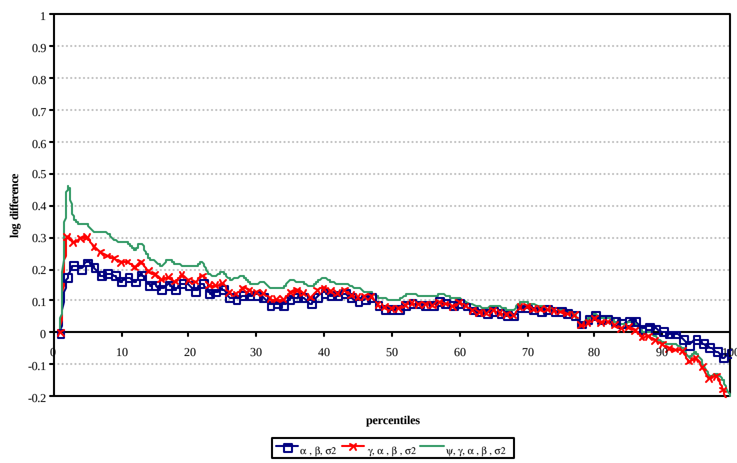


Figure 13: HOUSEHOLDS - Reducing illiteracy by 50%, β_{convex}

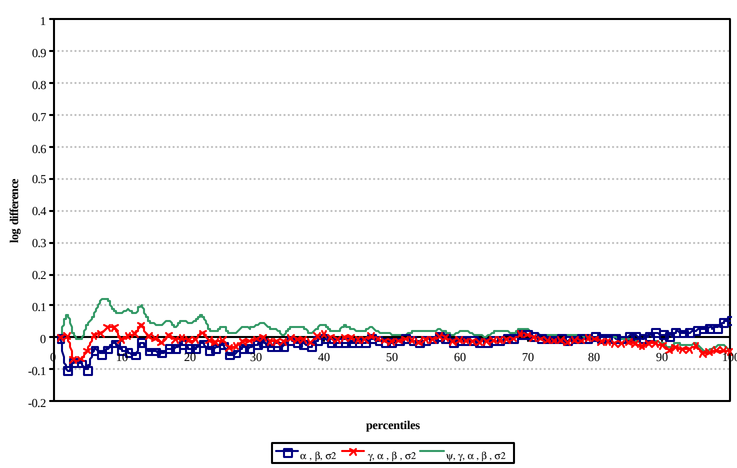


Figure 14: Net entrance into the wage sector per percentile

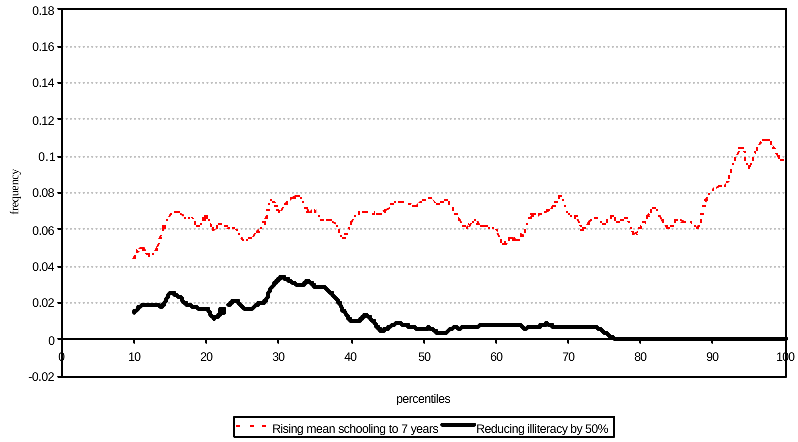


Figure 15: Net entrance into self-employment per percentile