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Introduction

There has long been a debate in the theoretical literature on inequality about whether inequality should be measured in terms of "outcomes" or in terms of "opportunities". The first definition refers to the joint product of the efforts of a person and the particular circumstances under which this effort was made, and most often consists of some income measure. The second definition refers precisely to those circumstances which are totally out of the control of a person but which nevertheless may significantly affect the results of his/her efforts and the efforts themselves. This distinction, the formulation of which is borrowed from Roemer (1998), building on earlier work by John Rawls, Amartya Sen and others, is well illustrated by the standard opposition between inequality and mobility. For instance, the US are often presented as more unequal than European societies but at the same time more mobile, the second quality being sometimes taken as the sign of a more equal distribution of chances and therefore a higher 'social justice'.[1]

Despite the obvious relevance of the concept of inequality of opportunities and implicitly of the question of social mobility, relative little evidence is available in this field of the economic literature.[2] Indeed, most of the economic literature on inequality focuses on the inequality of outcomes. The main reason for this is to be found in the difficulty of separating out 'circumstances' and 'efforts', since efforts themselves may sometimes be affected by circumstances, in the frequent unavailability of variables that could satisfactorily describe 'circumstances' and in scarce data sources on mobility. The latter problems are especially acute in developing countries, which explains that still less evidence is available for them. Yet, knowing what part of observed (outcome) inequality may be attributed to circumstances, or family background, is as important there as in richer countries. In particular, such knowledge should give information on efficient redistribution policies and the choice between redistributing current income or expand the opportunities of the poor through improving the accumulation of human capital among children.

In view of the very high level of (outcome) inequality in Brazil, the question arises of the proportion that is due to opportunities that individuals inherit from their parents and the proportion of observed inequality that is due to some dispersion in their efforts and in the results of these

[1] For comparisons of mobility between the US and European countries, see Burkhauser et al. (1998), or Checchi et al. (1999).

efforts. There are various ways to proceed to estimate these proportions. The first one consists of studying how and how much parents do invest in their children conditionally on some basic characteristics of the parents. A sufficiently detailed ‘schooling demand model’ may be used to do this. For instance, this is the approach chosen by Behrman, Birdsall and Skelezy (2000) in their study of comparative intergenerational education mobility in Latin America. The problem with that approach is that it only permits to study future social mobility, that is, the relation between the education of children, when they will be adults, and that of their parents. The approach we use in the present paper is of a different nature. We use direct information asked to survey respondents about the education of their parents in the household surveys (PNAD) taken in 1988 and 1996. On the basis of that information, it is then easy to measure intergenerational educational mobility as well as the way in which parents’ education affects directly or indirectly - through the education of the children - the earnings or income of the children. Moreover, by controlling by the year of birth, it is possible to see how both phenomena have changed over time. In turn this may lead to some speculation about why these changes occurred.

This analysis reveals a very sizeable inequality of opportunities in Brazil. On the one hand, parents’ education appears to be a powerful independent determinant of individual earnings besides individuals’ own education. On the other hand, parent education proves to be a powerful predictor of the education of children. In addition, estimated coefficients suggest that for older cohorts the relationship between the education of the parents and that of the children is close to one-to-one. In other words, one additional year of schooling for the parents means, on average, one additional year of schooling for children, so that the distribution is close to be fully reproduced – up to some common increment of schooling – across generations. The only positive note comes from the finding that educational mobility has significantly increased for the younger cohorts.

The paper is organized as follows. Section 1 shortly discusses the theoretical background of the estimation work undertaken in this paper, that is, the general relationship between inequality of outcomes, inequality of opportunities and intergenerational educational mobility, given the variables available in our database. Section 2 presents the regression results that are used to give a measure of the previous concepts. Section 3 gives measures of the inequality of opportunities and of mobility that makes rough comparisons with analogous indices in other countries. The

[2] By contrast, social mobility has always been a leading theme of the sociological literature. However, it is not clear

concluding section draws the implications of these results for our understanding of Brazilian inequality and policy.

1. Circumstances, efforts and intergenerational mobility

Among the determinants of the earnings of an active individual at some point of time, one may distinguish characteristics that are independent of the individual's will, which we shall call circumstances, following Roemer (1998), and characteristics that, on the contrary, reflect the 'efforts' made at increasing his productivity. Let denote C the first set of variables and E the second set. C will typically include fixed socio-demographic attributes like race, region of origin, and some characteristics of the individual's family background. E should include human capital accumulated by the individual since he/she is free to make decisions for himself/herself. Behind this, one may find part of formal schooling, but also on the job training, current work efforts or decisions like job changes or migrations.

Formally, let the following simple equation represent the interaction between circumstances, efforts and current (log) earnings, w, for an individual i:

$$Ln(w_i) = C_i.\alpha + E_i.\beta + u_i \qquad (1)$$

where α and.β are two vectors of coefficients and u_i is a residual term that includes unobserved circumstance and effort variables, sheer luck, measurement errors ,and temporary departures from the permanent level of earnings. All these factors are assumed to be orthogonal to the variables actually included in C and E. If we were to measure inequality by the variance of earning logarithms, and if it were possible to assume that circumstances and efforts are mutually independent, then we would have the following simple decomposition of total inequality:

$$v(Lnw) = \alpha'.V(C).\alpha + \beta'V(E)\beta + v(u) \qquad (2)$$

where v( ) stands for the variance of the variable in bracket and V( ) for the covariance matrix of all the variables in bracket. In other words, total inequality could be explained simply as the sum of

whether that literature translates easily into standard economic inequality concepts.

the inequality of opportunities (first term on the RHS), the inequality of efforts (seconds term) and the effect of unobservables. If one does not want to use the variance of logarithms as inequality index, then one could simulate the effects on the distribution of the log earnings among individuals of equalizing C or E across individuals, leading to the same type of decomposition as with the variance.

Two complications arise in the preceding framework if one assumes that there is no independence between circumstances and efforts, or between unobservables and observable earning determinants. Consider first that efforts are partly determined by circumstances. For instance, formal schooling is partly determined by family background. Assuming reasonably that unobserved effort determinants, v, are orthogonal to observed circumstances, this is equivalent to specifying a second model for efforts. For instance:

$$E'_i = C_i.b + v_i \qquad (3)$$

where b is a matrix of coefficients and v_i stands for a vector of unobserved effort determinants – one vector for each component of the effort vector, E. Substituting in (1), one gets:

$$Ln(w_i) = C_i.(\alpha + \beta.b) + (E_i - C_i.b).\ \beta + u_i \qquad (4)$$

Circumstances now have a double effect on earnings. They affect it directly, for given efforts. This corresponds to the set of coefficients α. They also affect it indirectly through their influence on efforts. This is the set of coefficients $\beta.b$. Of course, this modifies the decomposition formula (2) or the same type of decomposition applied to other inequality measures or to the full distribution of earnings.

The preceding decomposition is easy to implement, provided that one can rely on unbiased estimators of the various sets of coefficients, α, β and b. In turn this requires that the orthogonality assumption between u, C and E in equation (1) might be found satisfactory. This might be the case for the circumstance variables. After all, one may not be so much interested in the 'true' effect of the variables included in C but in their overall impact once their correlation with unobservable circumstances are taken into account. For instance, say that C include parents education but not their wealth. Then estimating (1) through standard regression techniques will give a biased estimate of the coefficient of parental education that will depend on the unobserved correlation between the education of the parents and their wealth. The coefficient matrix b will be biased in the same way and there will be a doubt in the decomposition of total inequality to what is the actual meaning of parental education. It is simply a matter of being aware of it.

Things are more serious when unobservables in the earning equations cannot be assumed to be independent of the effort variable. Again, imagine that the wealth of parents is important to determine both the schooling and the current earnings of their children, independently of their own education. This correlation between u and E, or equivalently between u and v is introducing some bias in the estimation of the β coefficients and therefore in the decomposition of the total inequality into a contribution due to circumstances and a contribution due to efforts.

One way out of this difficulty would be to observe instrumental variables, Z that would affect efforts but not earnings. Equation (3) would then be replaced by:

$$E'_i = C_i.b + Z_i.d + v_i \qquad (5)$$

Then, instrumenting the effort variables in (1) through (4) would yield an unbiased estimator of β and therefore, an unbiased decomposition of total inequality into inequality of opportunities and efforts. Models of this type have been extensively used in the return to education literature. In the standard Mincerian equation, it was thought that instrumenting education by family background would correct for obvious endogeneity biases of education. It was checked in a few countries that this was indeed the case. Then family background was considered as an independent earning determinant too, which required using additional instruments. Ability tests taken into school often played that role. However, not so many data sets had the relevant information, this problem being still more serious in developing countries.[3]

[3] Earlier contributions include Bowles (1972), Griliches (1972), Taubman (19..). For a brief survey of all models of returns to schooling based on this kind of instrumentation see Card (2001).

In the absence of adequate instrumental variables, Z, the only solution is simply to explore the likely effect of the potential bias in the estimation of β due to the correlation between u and v, and then to decide what is the most convincing outcome. This is what we shall do in the case of Brazil.

When circumstance variables include characteristics of parents, very much of the preceding analysis has to do with intergenerational mobility. We would certainly have a direct measure of income mobility if we had parents' income among variables C. We may have other types of mobility behind equations (3). For instance if parental education is among variables C and individuals' schooling is among the effort variables E, then part of system (3) actually describes educational mobility. The schooling of observed individuals is simply explained by that of their parents. The corresponding coefficient b gives an indication of the extent of mobility. For instance, if education is measured in number of years of schooling, then the extent to which b is less than unity would describe how quickly differences in education tend to systematically lessen across generations. In that sense, the inequality of circumstances or opportunities is clearly higher the less mobile is education across generations – i.e. the higher is the corresponding component of b. Of course, another source of mobility may be given by the residual term, v. It corresponds to the non-systematic part of mobility that is orthogonal to the concept of inequality of opportunities. Because of this, it may be of lesser interest in the present context. [4]

2. Parental education in earnings model and intergenerational educational mobility

The preceding methodology to distinguish between inequality of opportunities and inequality of outcomes is now applied to Brazilian data. This section first describes the data and the nature of the variables being used. It then discussed the various estimates obtained for the earning equations and for the equation describing intergenerational educational mobility.

Data and variables

Data are from the 1988 and 1996 waves of the Pesquisa Nacional por Amostragem a Domicilio (PNAD), the Brazilian Household Surveys conducted by the Instituto Brasileiro de Geografia e Estadistica (IBGE)[5]. For these two years, information about parental education of household heads and spouses is available. Information is also available on the occupation of the parents. The

[4] Although it is the center of analysis in Behrman, Birdsall and Szekely (2000).

analysis is restricted to urban areas because of imprecise income measurement in rural areas. It is also restricted to individuals 26 to 60 years old, in an effort to concentrate on individuals having finished schooling and still active in the labor market.

The analysis will be conducted by 5-year cohorts (from individuals born between 1936-40 up to those born between 1966-70). The reason for this choice is that this paper focuses not only on the extent of inequality of opportunities at a point of time and how it compares with the inequality of outcomes, but also to the long-run changes in the former inequality and intergenerational mobility. An important question is indeed whether the increase in the educational level of successive cohorts was accompanied by more or less educational mobility and a reduction in the inequality of opportunities. Comparing various cohorts observed at a single point of time permits following the long-run evolution of these social characteristics of the Brazilian society. It turns out that both the 1988 and 1996 surveys give a convergent view on cohorts that are common to the two surveys. Results that follow are based on the 1996 survey.

The earnings variable is defined as "all jobs real monthly earnings", measured in logarithms. No correction is made for the number of hours of work – this information was little reliable. This means that the earnings equation may include some labor supply features. The vector of circumstance variables includes race dummies, parental education expressed in numbers of years of schooling[6] (using the mean and difference between education of father and mother), the occupational position of the father (farmer or not), and dummies for the regions of origin. [7]

The vector of effort variables is restricted to the education of the individual, measured in years of schooling[8], and a migration dummy, defined as whether the municipality of residence was different from the one where born. Note, however, that this migration might have been done by the

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[5] 1988 data were also used to control for age effects and robustness of results.

[6] Parental education is given by discrete levels. They were converted in years of schooling (here in brackets) using the following rule : No school or incomplete 1st serie, 1st grade (0); Incomplete elementary or complete 1st to 3rd serie, 1st grade (2); Complete elementary, or complete 4th serie, 1st grade (4); Incomplete half 1st cycle or 5th to 7th serie, 1st grade (6); Complete half 1st cycle or complete 8th grade, 1st grade (8); Incomplete half 2nd cycle or incomplete 2nd grade (9.5); Complete half 2nd cycle or complete 2nd grade (11); Incomplete superior (13); Complete superior (15); Master or doctorate (17).

[7] A variable that was used in a first stage as a 'circumstance' variable was whether the individual was forced to work as a child – i.e. before 14 - or not. However, this variable proved to be too much related to the number of years of schooling to be of very much interest.

[8] The variable years of schooling provided in the PNAD is upper bounded at 15 years old. We used this variable, though gave 17 years of schooling to those individuals having done a master or a doctorate.

individual him/herself when adult or by his/her parents when he/she was a child. It should be taken as a circumstance variable in the second case. Unfortunately, there was no way this distinction could be made. Results obtained are more consistent with the effort interpretation of that variable.

In addition to the preceding list of variables, the selection equation used for correcting women earning equations for the standard participation bias uses the composition of family, the number of children and household income per capita – without own earnings – as instrumental variables. Summary statistics for all variables used in the analysis are shown in table 1.

Earnings equations

The earnings equations were estimated separately for men and women, and by cohort, using simple OLS for men and using the Heckman's two-stage participation bias correction procedure in the case of women[9]. Results are shown in tables 2.a. and 2.b. Note that, unlike with the standard Mincerian specification, age or experience does not appear among the regressors. This is because cohorts are homogeneous at this respect.

(Tables 2.a and 2.b)

All variables have the expected effect on earnings. Racial discrimination coefficients are significant and negative for black and 'pardo'. They are positive, but not always significant for people with an Asian origin 'yellows'. For women, however, it is interesting that discrimination is strong and significant for the first group (black) only in the youngest cohorts. The extent of discrimination is also less pronounced than for men. Regional differences are also important. Compared to the omitted regional area (South East), living in any other region has a negative effect for men, significant for nearly all cohorts except the older ones. For women this negative effect is also present though less often significant. The region that seems to have the worst effect on earnings is the North East.

The estimated effect of parental education on individual earnings is always positive, significant, and relatively stable across cohorts. It is also sizable since it amounts to 5 /6 per cent difference per year of schooling of the parents. The difference in the education of the father and the mother is meant to detect a possible asymmetry in the role of parents. But no such asymmetry seems to be present.

Turning now to the vector of "effort" variables, individuals' own education has the usual positive and significant effect on earnings. This effect does not seem to be stable across cohorts. But this may be due to the fact that the specification used here is not strictly equivalent to the standard Mincerian equation. The experience effect tends to raise the returns to education in older cohorts, which is exactly what is found here.[10]

More interesting is the fact that the order of magnitude obtained for the return to schooling seems to fall slightly below what may be found in comparable studies for Brazil. For instance, Ferreira and Paes de Barros (2000) find that the marginal return on a year of schooling is in the range 12 to 15 per cent for both men and women in 1999. A possible explanation of that difference may again lie in the specification being used. The specification used here is not strictly comparable to the Mincerian model, whereas Ferreira and Paes de Barros introduce the square of the number of years of schooling in their regression. More fundamentally, however, the difference found between the present study and previous ones is consistent with the likely over-estimation of the returns to schooling in the specification of an earning equation that does not include family background variables. Indeed, it may be expected in this case that omitted earnings determinants are positively correlated with the number of years of schooling, so that standard OLS estimation will tend to over-estimate the role of schooling. This expectation is confirmed by the data. Tables 3a and 3b show the results of estimating the preceding earning equation where years of schooling are instrumented using parental education and other exogenous variables, but where parental education is excluded from the list of regressors. The coefficient of the predicted number of years of schooling turns out to be substantially higher than in the previous case since it now partly accounts for the direct influence of parental education on individual earnings.

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[9] A standard Heckman correction was initially applied to men as well, but the correlation between the random terms of the participation condition and that of the earning equation is close to unity.

[10] In the conventional Mincerian specification : $Lnw = a.S + b.Exp - c.Exp^2$ with $Exp = Age - S - 6$ and a, b and c positive coefficients. It may be easily seen that the rate of return to the number of years of schooling, S, is indeed increasing with age.

Whatever the model being used, migration has a significant and positive effect on earnings, both for men and women. As mentioned above, this sign would be consistent with a human capital interpretation of migration and therefore migration being seen more as an effort variable than a circumstance variable.

Intergenerational Educational Mobility

The analysis now moves one step forward by examining the relationship between the schooling of individuals and that of their parents, so as to be able to measure the extent to which that variable results from circumstances or true efforts. This is equivalent with measuring the degree of intergenerational educational mobility.

Table 4 gives, for each cohort, the mean overall years of schooling as well as the mean years of schooling for various levels of the education of the father or the mother. The mean education level of the Brazilian society has increased steadily over time up to the youngest cohorts, when it has slightly decreased – although this may result from some people in that cohort still going to the university. Mean years of schooling by parental education levels across cohorts seems to suggest some recent increase in intergenerational educational mobility. In particular the number of years of schooling of those individuals with low educated parents increased more over the four or five last cohorts than for those individuals whose parents had a medium or high level of education.

(Table 4)

A more direct evaluation of intergenerational educational mobility is provided by a regression of type (3) where the education of individuals in the sample appears on the left hand side and all circumstance variables, including the number of years of schooling of the parents are on the right hand side. Regressions for the various cohorts are shown in table 4a and 4b separately for men and women. The comparison of these various results call for interesting remarks.

Intergenerational educational mobility is measured, negatively, by the coefficient of the number of years of schooling of parents. The higher that coefficient, the stronger is parental education in determining the schooling of their children, and therefore the less mobility there is. Because education is measured for both parents in years of schooling, a unit value for that coefficient is a convenient reference. It would correspond to the perpetuation of differences in years of schooling across generations. On the contrary, a coefficient less than unity means that educational differences tend to diminish across generations. From that point of view, a striking feature in tables 4a and 4b is that intergenerational mobility has been increasing monotonically across cohorts. Overall the gain is substantial. For people born in the early 1940s, a one-year difference in the education of their parents resulted in a difference of .8 years in their own schooling. For those born in the late 1960s, the same initial difference in parental education resulted in a little more than half year of schooling. From an educational point of view, the inequality of opportunities may thus have decreased significantly in Brazil over time.

Seeing in the preceding evolution essentially the result of a general spreading of education over time would not be totally justified. If most children are now going to school for 5 years whereas they were going to school only for 3 years 20 years ago, it is natural that the influence of parental education declined with time. But this should be true of the other circumstance variables too. This is not actually the case, however. The role of race, in particular, seems to have remained the same across cohorts – at least no clear trend seems to be present. Black people have the same quantitative disadvantage in education – 1 to 2 years of schooling- as they had in the 1940s or the 1950s. Likewise, the disadvantage of living in the North-East for men has remained approximately constant, the same being true of the father being a farmer. In other words, the equality of educational opportunities may have increased in Brazil with respect to educational family background, but not so much with respect to other family characteristics.

Another view at educational mobility consists of examining the relative importance of unobservables, including sheer luck, in determining educational attainments. This may be measured by the complement of the familiar R^2 statistic to unity. From that point of view, it may be seen in tables 4a and 4b that an upward trend seems to be present across cohorts – even when downplaying the sudden drop in the R^2 for the youngest cohort, which may be due to people still studying in that cohort. But that trend seems to be very slow and rather irregular.

Finally, an interesting feature of intergenerational educational mobility is that it seems to be influenced by intra-household decision mechanisms for women but not for men. In the case of women, the transmission of education from parents to children is higher when the educational disadvantage of the mother with respect to the father is low. This effect is significant and persistent across cohorts. This is not true for men, however. Mothers' education seems to weigh more than fathers' but the difference is significant only for a single cohort.

Another way of looking at intergenerational educational mobility is through the usual transition matrices. Matrices for four cohorts are shown in tables 7a-d, where the number of years of education is expressed as deviations from the mean. Intergenerational educational mobility has clearly increased for the less educated individuals (for the older cohorts, around 80% of those individuals whose parents had two or less years of education less than the mean, stayed at a similar position with respect to their own mean, while for the youngest cohort this percentage has fallen up to 55%). However, it has first decreased and then remained more or less constant for the group of higher-educated sons of higher-educated parents. Another interesting feature is the fact that a significant intergenerational downward mobility (with respect to the cohort mean) is observed for any cohort, though at a decreasing rate. These transition matrices serve to show that there exist important non-linearities in the relation between parental education and that of the sons that are not captured by the previous linear regression analysis.

Two last remarks must be made to place the preceding analysis in the proper perspective. First, very much of the preceding discussion is based on measuring education in terms of the number of years of schooling. One might prefer a more general approach where 'human capital' is what matters in intergenerational transmission mechanisms, human capital being measured by the cost of education, including foregone earnings, or possibly by the earnings that various educational levels actually command. The two approaches are equivalent when it is assumed that the rate of return to the number of years of schooling is constant, as done in the earning equations above. They are not if the marginal rate of return to an additional year of schooling depends on the level of schooling. Second, the quality of schooling is totally ignored in the preceding description of intergenerational educational mobility. It cannot be ruled out that taking into account the quality of education so as to get closer again to a concept of human capital would modify the preceding conclusions on increasing educational mobility in Brazil.[11] For both reasons, these conclusions must thus taken with very much care.

The issue of the schooling endogeneity bias

Before putting together the preceding earning and educational mobility equations to measure the inequality of opportunities, it is necessary to discuss the implications of the bias in the earning equation possibly arising from the endogeneity of the schooling variable. As said above, no variable is available in the data source being used for Brazil that would permit instrumenting the schooling variable in equation (1) so as to test for the existence of such a bias and to correct for it. However, various experiments were made on the basis of the preceding models which permitted to define useful benchmarks for the rest of the analysis.

Practically, the problem comes from a possible correlation between the variables which hide behind the residual, u_i, of equation (1) and the schooling variable, S_i, included in E_i. Let Cor(S, u) be that correlation, and let assume reasonably that the residual term is orthogonal to all other variables in the earning equation (1). Under these assumptions, it would be rather easy to estimate the bias arising in OLS estimates from the endogeneity of S if some estimate of Cor(S, u) were available. This bias is simply given by:

$$B = -\left[(C,E)'(C,E)\right]_S^{-1}.Cor(S,u).s_S.s_u \qquad (6)$$

where $\left[(C,E)'(C,E)\right]_S^{-1}$ is the S-row of the inverted covariance matrix of the regressors, and σ_S and σ_u are respectively the standard deviations of schooling and of the residual of the earning equation.

Without the possibility of estimating Cor(S,u) on Brazilian data, two solutions were explored : a) use a value estimated in another country; b) do sensitivity analysis to examine the potential size of the bias. It was possible to obtain an estimate of Cor(S, u) from a French study of intergenerational mobility where a model of the type (1)-(5) was estimated using parents' health and employment status at schooling age of the children as identifying instrumental variable Z.[12] It turned out that the resulting estimate of Cor(S,u) was negative and rather large – around -.7 .[13] A negative correlation

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11 For some references to the role of educational quality in shaping inequalities in Brazil see the motivation of the theoretical model in Ferreira (2000).

12 See Goux and Maurin (2001). We thank E. Maurin for running the necessary regressions to get an estimate of Cor(S, u). We are not aware of other studies in developed countries where such identification was possible.

13 Dummy variables for schooling achievements rather than years of schooling were used in the Goux-Maurin study. The common sign of the correlation between these dummy variables and the residual was taken as being the sign of

is not surprising. Somebody who expects high earnings, conditional on education, because of some unobserved earning determinant – for instance wealthy parents - has less incentives to be good in school than somebody without such expectations. The size of the correlation is more surprising. However, it turns out that this coefficient, as well as the coefficients of the earning equation when schooling is properly instrumented, is very imprecisely estimated, reflecting the limited explanatory power of the instrumental variables. Overall, the lesson to be drawn from this experiment with French data thus is that Cor(S, u) is likely to be negative and 'sizable'.

A simple sensitivity analysis suggests that the extent of the schooling endogeneity bias in Brazil is likely to be limited. The analysis consisted of evaluating the bias given by (6) conditionally on alternative values of Cor(S, u). These values were chosen negative, as suggested by the experiment with French data. As the absolute value of Cor(S, u) is allowed to increase, the corrected coefficient of schooling in model (1) starts to increase, as the negative bias is corrected for. At the same time, however, the (unbiased) estimate of the coefficient of parental education is becoming smaller. At some stage, that estimate even becomes negative. As the hypothesis that more educated parents could cause lower earnings for their children – conditionally on the education and other characteristics of the children – seemed untenable, the corresponding absolute value of Cor(S, u) was taken to be a natural upper limit. It turns out to be rather low, certainly much lower than the .7 value obtained with French data. Tables 5 a and 5b show that the consistency limit – near zero coefficients for parental education – is obtained at Cor(S, u) = .2 for men and .1 for women. Not surprisingly these coefficients are not far from those obtained above in tables 3a and 3b when parental education was excluded from the earning equation.

(Tables 5a and 5b around here)

This sensitivity analysis suggests that the two sets of earning equations estimated above in tables 2 and 3 provide natural benchmarks for the treatment of the endogeneity bias of the schooling variable. The OLS estimates shown in table 2 with parental education among the regressors are obtained under the assumption that there is no such bias, whereas the TSLS estimates shown in table 3 with parental education excluded from the regressors practically correspond to the case

Cor(S, u). For the absolute value of the correlation coefficient, we simply used the square root of the R^2 of the regression of u on the educational achievement dummy variables.

where the endogeneity bias is such that it explains by itself all of the initial direct effect of parental education on childrens' earnings.

3. Simulating the effects of the inequality of opportunities linked to parental education

The preceding models relate current earnings and schooling to circumstances or opportunities as represented by parental education, race and region of birth. They also provide simple ways of measuring the effect of the inequality of opportunities upon the inequality of current earnings.

To see how this may be done, the two basic equations (1) and (3) above are first rewritten with all circumstance and effort variables being made explicit.

$$Ln(w_i) = a_0 + R_i a_R + GR_i.a_G + MPE_i.a_P + DPE_i.a_D + FO_i.a_F + S_i.b_S + M_i.b_M + u_i \tag{7}$$

$$S_i = a_0 + R_i a_R + GR_i.a_G + MPE_i.a_P + DPE_i.a_D + FO_i.a_F + v_i \tag{8}$$

where R, GR, MPE, DPE and FO stand respectively for the race dummies, the regional dummies, mean parental education, the mother/father difference in education, and father occupation, whereas S is the number of years of schooling and M the migrant status. α_R , α_G , a_R , and a_G are vectors of coefficients whereas other parameters are scalars.

An appealing way of measuring the inequality of opportunities consists of evaluating what would be the distribution of earnings in the preceding system of equations if all the inequality due to the effort variables had been eliminated. For instance, it is tempting to simply equalize the S_i and the M_i in (7) and/or or to replace S_i by the predicted value given by (8). But then, a decision must be taken with respect to the two residual terms. If they are both interpreted as pure circumstance variables, inequality with respect to S_i must then be fully considered as inequality of opportunities, and the only effort variable in (7) would be the migration status. On the contrary, if one considers that the two residuals reflect pure efforts, they must be taken away when evaluating the inequality of opportunities. In that case, S_i in (7) should be replaced by its predicted value in (8) and both M_i and u_i should be ignored in (7).

There is something arbitrary in deciding that the residual terms reflect inequality of opportunities or inequality of outcomes, or some combination of both. Because of this, it may be simply impossible to measure the 'total' contribution of the inequality of opportunities to observed inequality. This does not prevent to measure the contribution of a particular observed circumstance variable, though. For instance, one may want to limit the analysis to the contribution of race, parental education, or even individual schooling in the case where one considers that all of that variable is determined by circumstances rather than efforts. In both cases, it is sufficient to look at the distribution of earnings when R_i is equalized across individuals in both equations (7) and (8), or when MPE_i and DPE_i are equalized. This is the approach being used in what follows, focusing on the role of individual schooling and parental education.

Even with this partial approach, additional assumptions are necessary. First, one must decide whether to use the earning equation with parental education among the regressors – table 2 - or the earning equation corrected for the endogeneity bias of schooling – table 3 - which was shown above to be close to the earning equation without parental education. Second, an assumption must be made about what seems a satisfactory counterfactual for the 'equality' of opportunities. It is computationally simple to assume that the variable of interest would be equally distributed in the absence of inequality of opportunities. This may not be very realistic, though. Inequality of earnings in Brazil would certainly be considerably diminished if individual schooling levels were the same. But, practically, this is a hypothetical counterfactual which says little about how much gain in equality could be obtained by making the distribution of individual schooling or parental education 'reasonably' less unequal. Thus, some benchmark distribution of schooling and/or parental education must be defined to identify in a realistic way the potential gains to be obtained from equalizing the distribution of opportunities. The change from the original distribution of education to the benchmark distribution is done using the now standard methodology of rank preserving changes. In other words, the most educated in the original distribution is given the education of the most educated in the benchmark distribution, then the second most educated in the original distribution is given the education of the second most educated, etc… The benchmark distributions used below are defined as follows.

First, instead of equalizing all educational levels, a lower bound is introduced that is equivalent to equalize only the bottom of the distribution. Practically, all schooling levels less than 8 years of schooling are raised to 8 years for children, and parental education less than 6 years of schooling is replaced by 6 for parents. This is equivalent with using as a reference a situation where some compulsory schooling requirements would be implemented without affecting the schooling attainment of those staying in school beyond compulsory age. The difference between parents and children is introduced only to reflect the fact that it would take much more time to 'equalize from the bottom' the distribution of schooling among parents than among younger cohorts. Note, though, that the minimum schooling level chosen do not seem to be out of reach.[14]

This first set of benchmark distributions are based on a modification of the bottom of the distribution of schooling but leaves observed schooling attainments above the minimum unchanged. But it is unlikely that the top of the distribution of schooling levels will remain in the future what they were in the past 20 or 30 years ago. Thus, a second set of benchmark distributions has been obtained by the 'equalizing from the bottom' procedure applied to the distribution of schooling and parental education observed for the younger cohort in the sample - i.e. the 1966-70 cohort. In other words, it is assumed that a reasonable reference distribution for schooling and parental education when simulating more equal opportunities in the distribution of schooling and parental education in the youngest cohort after imposing the 6 and 8 years lower bounds. This gives to the simulations made on past cohorts some kind of forward-looking dimension.

Table 6 summarizes the results that have been obtained by simulating these changes in schooling or parental education with the models which were previously estimated. Part a of the table refers to the case where parental education is excluded from the regressors in the earning equation, whereas part b covers the other polar case where parental education is present in the earning regression and schooling is taken to be exogenous. Given the methodology that is being used, it would be possible to compare the complete distribution of earnings for each cohort under alternative simulation scenarios. For simplicity, however, only two usual summary inequality figures (Gini and Theil) are reported in the tables.

The first part of table 6a is strictly equivalent to measuring the contribution of schooling to the inequality of individual earnings. Schooling is taken to be a pure circumstance variable. In other words, all the variables on the right hand side of (8), including unobserved variables behind v, are

[14] In effect, universal schooling until the age of 14 has often been mentioned as the proximate target in educational

taken to be beyond individual control. The drop in inequality obtained by equalizing schooling levels is dramatic. Except for the youngest cohorts, the Gini coefficient would fall by more than 10 percentage points and the Theil index by more than 20 for men, these figures being still larger for women. This is a confirmation of the major role played by education in explaining the sources of inequality in Brazil - see for instance, Ferreira and Paes de Barros (2000). As could be expected, the fall in inequality is smaller when education equalizing takes place only at the bottom of the distribution, that is, assuming that compulsory schooling until 14 could have been successfully implemented at the time the various cohorts were at schooling age. The drop in inequality is only reduced by approximately one third and remains very large. Finally, no big change is obtained when the underlying distribution of schooling, above the minimum, is assumed to be the distribution observed for the youngest cohort. All these results are consistent with the commonly accepted idea that a large part of earning inequality in Brazil is due to the educational deficit of an important part of the population.

The second part of table 6a goes deeper into the analysis by investigating the effects of eliminating that part of individual schooling inequality that may be traced back to differences in parental education. It thus indicates how much of today's earning inequality is explained by the intergenerational transmission of education, depending on the cohort being considered. Comparing rows (i) and (v), it may be seen that approximately half the inequality of earnings due to differences in individual schooling levels is actually inherited from the previous generation, this proportion being on average substantially higher for women. This may be seen as very much but there are various ways of interpreting that result. It may be taken as indicative of the potential effect of policies that would contribute to lessen the effect of parents' education on children's schooling attainment. The whole problem would then be that of the nature of these policies, an issue that goes beyond the scope of this paper. The preceding figures may also be taken as indicative of the kind of acceleration of inequality reduction that could go through intergenerational mechanisms. If schooling inequality is reduced today, independently of family background, in the younger cohorts, then it will be further reduced among the children of those cohorts. In that perspective, however, full equalization of parental education is not a very good reference. Partial equalization from the bottom (row vi) or the distribution of parents' education in the youngest cohorts is more relevant (row vii). Not

policy.

surprisingly, equity gains remain very high only for the oldest cohorts because for which the distribution of parental education is more unequal or very far from what may be observed in the youngest cohorts. However, with 2 points drop or more in the Gini coefficient, the equity gain from partial equalization of parental education remains non-negligible even for intermediate cohorts. Interestingly enough, some difference appears between men and women when the distribution of parental education in the youngest cohort is taken as a reference. In the case of women, this sometimes tends to increase inequality. The explanation of this lies in the fact that changes in intra-household educational differences are not taken into account in the present simulation, although it was seen above they were an important explanatory factor of women's schooling achievements.

The same scenarios about the determinants of schooling are considered in the case where the earning equation depends on both parental education and schooling. In that case, however, an additional distinction must be made. It is whether parental education influences the distribution of earnings directly, or indirectly through the schooling of individuals - in the case schooling is not considered as fully determined by circumstances. The direct role of parental education in earnings inequality is obtained by equalizing completely or partially that variable in the earning equation but keeping individual schooling unchanged. This is equivalent with taking schooling as independent of parental education. The indirect effect of parental education on earning inequality may then be evaluated by comparing its total influence and its impact on through the earning equation.

Taking both parental education and schooling in the earning equation as reflecting pure circumstance variables leads to a contribution of the inequality of opportunities related to education comparable to what was obtained with the pure schooling model. Indeed the difference between rows (i), (ii) and (iv) of table 6b and 6a appears extremely limited. In other words, the earning model with the schooling variable as sole educational variable captures well the joint influence on the distribution of earnings of parental education and own schooling. Measured one way or another, the overall contribution of these two variables is undoubtedly very big. However, the two models are certainly not equivalent, as can be seen from row (iii). Modifying the whole distribution of both schooling and parental education - rather than equalizing it partly or partially - in the model with both parental education and schooling has a rather different effect on the distribution of earnings than modifying the distribution of schooling in the model with no direct effect of parental education.

The second part of table 6b confirms this asymmetry in the role of parental education and own schooling. Rows (v) to (viii) show the role of parental education both through schooling and directly on earnings. This role is unambiguously stronger than when it was restricted to the former, even though the elasticity of earnings with respect to schooling was then higher. For men, the inequality of opportunities through parental education alone now corresponds on average to 8 points in the Gini coefficient when full equalization is taken as a reference and 5 points when equalization is only partial. These figures were 2 points lower in table 6a. The difference is still higher for women. Based on these estimates, *it appears that 80 per cent or more of the contribution of education to earnings inequality*, as it appears in the first part of table 6a, *is to be explained directly or indirectly by parental education.* This leaves little room to the other determinants of schooling.

The relative contribution of the direct and indirect effect of parental education to earnings inequality may be appreciated by comparing the last row of table 6b (full equalization result) to row (v). It may be seen there that the direct effect of parental education on earning inequality is only slightly below the total effect shown in row (v). Based on the assumption that, conditionally on parental education, schooling is an exogenous determinant of earnings, the figures reported in table 6b thus suggests that it is not so much through better schooling achievements that the inequality of parental education is transmitted to the earnings of their children than through other unobserved channels. The role of the schooling channel is not negligible, however. This is quite the contrary. On average across cohorts, it amounts to something like 2 percentage points in the Gini coefficient for men and 3/4 points for women.

(Tentative) Conclusion

Not surprisingly, the existence of a possible bias in the estimation of the role of schooling in the determination of earnings translates at the simulation stage in ambiguous results about the way through which parental education and the corresponding inequality of opportunities affects the inequality of earnings. Assuming no bias leads to conclude that parental education increases earning inequality mostly through channels that are independent of schooling. At the other extreme, we considered in this paper the case where all of its effect on earnings would go through determining the schooling of children. Behind this ambiguity, however, some convergent results emerge. They are the following.

- Altogether, the inequality of opportunities that go through parental education may be responsible for a very substantial proportion of total inequality in Brazil. Parental education and/or schooling are jointly responsible for approximately 10 percentage points in the Gini coefficient of individual earnings, this percentage being higher for older cohorts and for women. Out of this, 60 to 80 per cent may be attributed to parental education.

- The preceding figures are based on a reference situation where schooling and parental education could be fully equalized within a cohort. Alternative references, in particular partial equalization through lower bounds would lead to a smaller overall contributions.

- Parental education affects earning inequality either directly or indirectly through schooling. The exercise undertaken in this paper suggests that the latter effect is *not smaller* than 2 percentage points in the Gini coefficient for men and 3/4 points for women. The midpoint of the confidence interval that corresponds to the two polar cases considered in this paper would thus be around 4 percentage points for men and 5/6 for women. This is certainly not a small effect and should justify policies aimed at giving more autonomy to own schooling decisions.

- Successive cohorts faced different situations in terms of inequality of opportunities. Intergenerational educational mobility has increased over time, especially at the bottom of the distribution. Equivalently, the education of the parents became a less powerful predictor of the education of their children over time. For the moment, this evolution does not reflect itself completely in the evolution of earning inequality across cohorts. This is because the rate of return to schooling and therefore the inequality of earnings is strongly age dependent. Yet, it is to be expected that because of that evolution earnings inequality along the life cycle will be smaller for younger cohorts. This point has to be checked by comparing cohorts when they have the same age and requires additional data.

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Table 1: Descriptive statistics.

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Mean all jobs earnings	263.4	410.2	528.6	566.1	516.4	453.8	344.1
Mean years of schooling	4.3	5.2	5.8	6.6	7.0	7.3	7.1
Mean father's years of schooling	2.2	2.5	2.6	2.8	3.0	3.3	3.3
Mean mother's years of schooling	1.7	1.9	2.2	2.3	2.6	3.0	3.0
% of population by race							
Branca (whites)	58.7%	58.4%	57.9%	57.8%	56.4%	57.0%	54.2%
Preta (blacks)	6.9%	7.3%	6.7%	6.5%	6.2%	5.8%	5.8%
Amarela (Asians)	0.7%	0.6%	0.6%	0.4%	0.3%	0.3%	0.3%
Parda (MR)	33.7%	33.8%	34.7%	35.3%	37.1%	36.9%	39.7%
% of population by regional area							
North	6.3%	6.4%	7.1%	7.5%	7.9%	8.0%	8.5%
North East	25.6%	26.2%	25.5%	24.1%	25.0%	25.3%	27.5%
South East	40.4%	40.0%	39.4%	39.3%	37.7%	37.0%	33.3%
South	18.6%	18.0%	18.0%	19.1%	18.9%	18.7%	18.3%
Center-West	9.0%	9.5%	10.0%	10.0%	10.6%	11.0%	12.5%
Share of migrants	70.6%	69.0%	67.7%	65.8%	61.8%	58.2%	56.2%
Share of sons of farmer father	58.6%	54.7%	49.2%	45.3%	40.3%	35.5%	32.6%
% of family type							
Couple, no children	23.4%	14.1%	9.3%	6.5%	6.2%	8.1%	13.7%
Couple with children	52.5%	64.8%	72.7%	78.4%	79.7%	78.7%	72.7%
Mother with children	12.9%	12.6%	11.5%	10.5%	9.3%	8.2%	7.8%
Other	11.3%	8.6%	6.6%	4.7%	4.8%	5.0%	5.8%
Share of Agricultural workers	15.5%	12.0%	8.0%	5.9%	5.3%	5.0%	5.0%

Table 2.a: Earnings regressions by cohort using OLS, for MEN.

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Race							
Branca (omitted)							
Preta	-0.422*	-0.362*	-0.283*	-0.317*	-0.244*	-0.208*	-0.306*
	(0.09)	(0.07)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)
Amarela	0.048	0.425*	0.791*	0.098	0.314*	0.320	-0.347
	(0.23)	(0.16)	(0.14)	(0.14)	(0.13)	(0.17)	(0.20)
Parda	-0.261*	-0.330*	-0.221*	-0.235*	-0.158*	-0.191*	-0.195*
	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Parental schooling							
Mean parental sch.	0.053*	0.047*	0.054*	0.047*	0.042*	0.049*	0.049*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Diff. Parental sch.	0.012	0.006	0.012*	0.006	0.000	-0.001	0.007
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Region dummies							
South East (omitted)							
North	-0.125	-0.067	-0.142*	-0.138*	-0.182*	-0.156*	-0.173*
	(0.11)	(0.09)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)
North East	-0.328*	-0.266*	-0.320*	-0.387*	-0.357*	-0.408*	-0.424*
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
South	-0.227*	-0.109*	-0.147*	-0.084*	-0.114*	-0.128*	-0.155*
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Center-West	-0.113	-0.042	-0.005	-0.144*	-0.037	-0.080*	-0.079*
	(0.09)	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Years of schooling	0.113*	0.111*	0.113*	0.109*	0.101*	0.097*	0.082*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Migrant dummy	0.038	0.209*	0.119*	0.077*	0.076*	0.085*	0.104*
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Agriculture dummy	-0.284*	-0.295*	-0.322*	-0.266*	-0.459*	-0.279*	-0.294*
	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Constant	5.597*	5.576*	5.630*	5.675*	5.620*	5.514*	5.525*
	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Sample size	1603	2337	3556	4623	5219	5308	4254
F-test	116.69*	168.2*	298.24*	332.27*	361.97*	372.31*	243.75*
R-squared	0.468	0.465	0.503	0.464	0.455	0.458	0.408
Adj R-squared	0.464	0.462	0.501	0.462	0.454	0.456	0.407

Table 2.b: Earnings regressions by cohort using Heckman correction (2SLS), for WOMEN.

Earnings Equation	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Race							
Branca (omitted)							
Preta	0.065	-0.110	-0.095	-0.166*	-0.230*	-0.213*	-0.118
	(0.15)	(0.10)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Amarela	-0.078	-0.266	0.068	0.406	0.253	0.400	0.070
	(0.45)	(0.31)	(0.20)	(0.21)	(0.19)	(0.25)	(0.21)
Parda	0.008	-0.145*	-0.143*	-0.230*	-0.125*	-0.181*	-0.109*
	(0.08)	(0.06)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Parental schooling							
Mean parental sch.	0.062*	0.053*	0.053*	0.040*	0.059*	0.067*	0.057*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Diff. Parental sch.	0.019	-0.008	0.002	-0.005	0.007	-0.007	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Region dummies							
South East (omitted)							
North	-0.493*	0.004	-0.025	-0.038	-0.110*	-0.022	-0.116*
	(0.19)	(0.10)	(0.08)	(0.06)	(0.05)	(0.05)	(0.06)
North East	-0.362*	-0.317*	-0.333*	-0.310*	-0.386*	-0.322*	-0.352*
	(0.10)	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
South	-0.197*	-0.043	-0.023	-0.092*	-0.042	-0.037	-0.018
	(0.09)	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Center-West	-0.153	0.031	-0.040	-0.054	-0.039	-0.030	-0.132*
	(0.13)	(0.09)	(0.07)	(0.05)	(0.04)	(0.04)	(0.05)
Years of schooling	0.111*	0.128*	0.126*	0.128*	0.124*	0.106*	0.104*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Migrant dummy	0.184*	0.106*	0.128*	0.095*	0.135*	0.092*	0.149*
	(0.07)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Agriculture dummy	0.019	-0.242	-0.151	0.083	-0.020	-0.101	-0.012
	(0.32)	(0.31)	(0.26)	(0.26)	(0.20)	(0.21)	(0.21)
Constant	3.924*	4.283*	4.573*	4.747*	4.490*	4.705*	4.733*
	(0.38)	(0.20)	(0.13)	(0.10)	(0.11)	(0.10)	(0.12)
Mills lambda[b]	0.567	0.336 *	0.147	0.023	0.190 *	-0.066	-0.186 *
	(0.25)	(0.14)	(0.10)	(0.08)	(0.08)	(0.07)	(0.08)
Rho	0.586	0.410	0.186	0.029	0.245	-0.089	-0.261
Sigma	0.968	0.818	0.791	0.792	0.777	0.742	0.713
Number of obs	3686	4201	5560	6663	7814	8204	7385
Censored obs	774	1268	2236	3213	3838	3753	2822
Uncensored obs	2912	2933	3324	3450	3976	4451	4563

[b]) Selection model includes all variables in earning equation plus family composition and total income per capita of other family members.

Table 3.a. Earnings equations excluding parental education, MEN (OLS)

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Race							
Preta	-0.383*	-0.325*	-0.248*	-0.258*	-0.115	-0.130*	-0.242*
	(0.10)	(0.09)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)
Amarela	-0.206	0.349	0.719*	-0.115	0.247	0.228	-0.518*
	(0.27)	(0.21)	(0.18)	(0.17)	(0.16)	(0.20)	(0.25)
Parda	-0.205*	-0.254*	-0.160*	-0.164*	-0.108*	-0.093*	-0.155*
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Region dummies							
South East (omitted)							
North	-0.234	-0.181	-0.154	-0.242*	-0.150*	-0.198*	-0.176*
	(0.13)	(0.11)	(0.09)	(0.07)	(0.06)	(0.06)	(0.06)
North East	0.027	0.028	0.149	0.088	0.160*	0.174*	0.146*
	(0.13)	(0.11)	(0.08)	(0.07)	(0.06)	(0.05)	(0.05)
South	-0.161	-0.039	0.031	0.033	0.053	0.039	0.011
	(0.14)	(0.11)	(0.09)	(0.07)	(0.06)	(0.06)	(0.06)
Center-West	-0.035	0.059	0.139	-0.026	0.127	0.069	0.081
	(0.16)	(0.13)	(0.10)	(0.08)	(0.07)	(0.06)	(0.06)
Predicted yschl [a]	0.161*	0.154*	0.161*	0.154*	0.148*	0.160*	0.154*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Migrant dummy	0.086	0.188*	0.147*	0.073*	0.089*	0.090*	0.129*
	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Agriculture dummy	-0.355*	-0.402*	-0.470*	-0.455*	-0.611*	-0.408*	-0.394*
	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Constant	5.357*	5.386*	5.271*	5.373*	5.205*	4.986*	4.957*
	(0.14)	(0.12)	(0.10)	(0.08)	(0.07)	(0.07)	(0.07)
Sample size	1417	2071	3129	4150	4597	4755	3795
F-test	74.04	104.98	189.34	193.46	237.99	257.58	183.21
R-squared	0.345	0.3376	0.3778	0.3185	0.3416	0.3519	0.3262
Adj R-squared	0.3403	0.3344	0.3758	0.3169	0.3402	0.3505	0.3244

[a]) Instrumented with other exogenous variables and parental education

Table 3.b. Earnings equations excluding parental education, WOMEN (2SLS)

Earnings Equation	**b1936_40**	**b1941_45**	**b1946_50**	**b1951_55**	**b1956_60**	**b1961_65**	**b1966_70**
Race							
Preta	-0.023	-0.162	-0.005	-0.289 *	-0.198 *	-0.080	-0.020
	(0.16)	(0.12)	(0.10)	(0.09)	(0.07)	(0.08)	(0.09)
Amarela	0.120	-0.122	0.019	0.216	0.036	0.103	0.090
	(0.47)	(0.36)	(0.25)	(0.30)	(0.22)	(0.28)	(0.32)
Parda	0.010	-0.153 *	-0.084	-0.191 *	-0.087	-0.104 *	-0.040
	(0.09)	(0.07)	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)
Region dummies							
South East (omitted)							
North	-0.038	-0.245 *	-0.406 *	-0.350 *	-0.228 *	-0.324 *	-0.157 *
	(0.22)	(0.12)	(0.10)	(0.09)	(0.06)	(0.06)	(0.08)
North East	0.233	0.039	-0.081	-0.059	0.155 *	0.002	0.143
	(0.22)	(0.12)	(0.10)	(0.09)	(0.06)	(0.06)	(0.08)
South	0.013	0.023	-0.072	-0.052	0.076	-0.020	0.179 *
	(0.22)	(0.13)	(0.10)	(0.09)	(0.07)	(0.07)	(0.08)
Center-West	0.103	0.071	-0.072	-0.077	0.121	-0.037	0.013
	(0.25)	(0.15)	(0.11)	(0.10)	(0.07)	(0.07)	(0.08)
Predicted yschl [a]	0.149 *	0.155 *	0.162 *	0.151 *	0.171 *	0.194 *	0.176 *
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Migrant dummy	0.145	0.113	0.144 *	0.089 *	0.103 *	0.083 *	0.128 *
	(0.08)	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
Agriculture dummy	-0.155	-0.325	-0.348	-0.312	-0.305	-0.223	-0.311
	(0.33)	(0.37)	(0.30)	(0.31)	(0.24)	(0.25)	(0.23)
Constant	4.334 *	4.701 *	4.677 *	4.909 *	4.310 *	4.157 *	4.106 *
	(0.30)	(0.16)	(0.14)	(0.14)	(0.11)	(0.11)	(0.14)
Mills lambda[b]	0.348	-0.489	-0.210	-1.252 *	-0.083	-0.290	-0.843 *
	(0.36)	(0.27)	(0.24)	(0.32)	(0.22)	(0.21)	(0.24)
Rho	0.382	-0.529	-0.232	-1.168	-0.095	-0.348	-0.950
Sigma	0.910	0.924	0.907	1.072	0.869	0.834	0.887
Number of obs	824	1279	2155	3061	3594	3550	2726
Censored obs	691	1132	1965	2855	3365	3328	2517
Uncensored obs	133	147	190	206	229	222	209
Wald chi2(18)	155.13 *	348.18 *	663.72 *	627.98 *	1197.98 *	1359.39 *	575.89 *

[a]) Instrumented with other exogenous variables and parental education

[b]) Selection model includes all variables in earning equation plus family composition and total income per capita of other family members.

Table 4: Years of schooling, by cohort and parental education level.

Cohorts	Total Population	By Father's education level				By Mother's education level			
		None	Low	Medium	High	None	Low	Medium	High
b1931_35	1.64	1.87	4.09	6.62	11.49	2.12	4.03	7.23	11.25
b1936_40	4.26	2.15	4.71	7.50	10.97	2.47	4.56	7.82	10.84
b1941_45	5.02	2.63	5.54	8.24	12.19	2.99	5.56	8.59	12.18
b1946_50	5.75	3.24	5.95	8.90	12.61	3.44	5.86	9.16	12.54
b1951_55	6.46	4.02	6.62	9.23	12.40	4.19	6.53	9.41	12.40
b1956_60	6.93	4.39	6.95	9.39	12.56	4.38	6.83	9.34	12.52
b1961_65	7.29	4.63	7.25	9.50	12.23	4.87	7.06	9.38	12.11
b1966_70	7.12	4.84	6.97	9.00	11.56	4.89	6.79	8.87	11.53

Table 5.a: Educational mobility OLS regressions by cohort : men's years of schooling.

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Race							
Branca (omitted)							
Preta	-1.5353*	-1.3144*	-1.2426*	-1.444*	-1.955*	-1.7336*	-0.9481*
	0.40161	0.33269	0.29019	0.25134	0.24334	0.22654	0.23736
Amarela	2.90506*	2.209*	1.15887	2.52219*	2.02075*	3.34613*	0.05261
	1.06643	0.7552	0.70505	0.69554	0.66596	0.86493	1.03381
Parda	-0.8884*	-1.4307*	-1.2663*	-1.3163*	-1.2381*	-1.4229*	-0.8473*
	0.22398	0.18974	0.16	0.13865	0.12403	0.11535	0.1243
Parental schooling							
Mean parental sch.	0.8322*	0.81859*	0.77929*	0.72054*	0.68005*	0.62526*	0.55835*
	0.04176	0.03031	0.02463	0.02141	0.01747	0.01537	0.01711
Diff. Parental sch.	0.06993	0.01875	0.07138*	0.00886	-0.0105	0.02037	0.00473
	0.04236	0.03566	0.02825	0.02457	0.01967	0.01766	0.01917
Region dummies							
South East (omitted)							
North	-1.7653*	-0.7473	0.0558	-0.144	-0.0374	0.1629	0.04121
	0.47719	0.39584	0.34043	0.2726	0.2365	0.23111	0.24214
North East	-0.918*	-0.5683*	0.06103	-0.5601*	-0.5123*	-0.3978*	-0.8209*
	0.25326	0.20793	0.17913	0.16283	0.14514	0.13663	0.14518
South	-0.2519	-0.3528	-0.1366	-0.3291*	0.06086	0.08738	-0.1356
	0.25374	0.21997	0.18342	0.15076	0.1379	0.13004	0.14353
Center-West	-0.1172	0.08422	0.42427	0.26365	0.18344	0.47626*	-0.1038
	0.40608	0.33413	0.27004	0.23502	0.20871	0.18975	0.19434
Farmer father dummy	-2.3143*	-2.1686*	-2.6716*	-2.1751*	-2.0722*	-1.7032*	-1.5542*
	0.20656	0.1755	0.14531	0.12462	0.11279	0.10898	0.11806
Constant	5.31618*	5.75291*	6.26165*	6.75681*	6.80866*	6.81866*	6.60681*
	0.22013	0.18008	0.14961	0.1256	0.11441	0.10463	0.11586
Sample size	1515	2172	3233	4241	4670	4824	3840
F-test	118.79	186.53	283	296.23	376.03	353.48	219.53
R-squared	0.4413	0.4633	0.4676	0.4119	0.4466	0.4234	0.3644
Adj R-squared	0.4376	0.4608	0.466	0.4105	0.4454	0.4222	0.3627

Table 4.b: Educational mobility OLS regressions by cohort : women's years of schooling

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
Race							
Branca (omitted)							
Preta	0.32339	-1.246*	-2.2411*	-1.145*	-1.9592*	-1.5565*	-1.5864*
	0.49106	0.43812	0.34532	0.29632	0.27487	0.30065	0.30405
Amarela	1.59679	0.91742	2.84117*	0.13418	2.47012*	2.85256*	-0.12
	1.22848	0.96816	0.72754	0.91394	0.83169	0.96109	1.11167
Parda	-0.6459*	-0.8099*	-1.5975*	-1.4629*	-0.9801*	-1.0858*	-1.1627*
	0.27348	0.27314	0.197	0.1668	0.14551	0.14335	0.15992
Parental schooling							
Mean parental sch.	0.87009*	0.7963*	0.75509*	0.68058*	0.66481*	0.59318*	0.53123*
	0.04696	0.04455	0.0307	0.02445	0.02101	0.01854	0.02024
Diff. Parental sch.	0.10504*	-0.0438	0.06715*	0.09153*	0.08504*	0.04038*	0.06231*
	0.04824	0.0473	0.03318	0.02613	0.02223	0.02014	0.02212
Region dummies							
South East (omitted)							
North	-0.2748	0.11266	0.80034*	0.46993	0.70387*	0.35924	0.52507
	0.64808	0.55697	0.40251	0.3338	0.28539	0.28083	0.31721
North East	0.14084	0.23782	0.60151*	0.73219*	0.32328	0.24126	-0.1331
	0.29849	0.29089	0.21651	0.18904	0.16719	0.16232	0.18052
South	0.0375	-0.0568	-0.3631	-0.2138	0.17187	0.00608	-0.2256
	0.30058	0.30286	0.21842	0.18841	0.16316	0.15801	0.17504
Center-West	0.23967	-0.1775	0.41884	1.07792*	0.45269	0.48883*	0.43517
	0.50356	0.47346	0.34428	0.28659	0.23427	0.23054	0.24095
Farmer father dummy	-2.1117*	-2.3915*	-2.878*	-2.46*	-2.227*	-2.0568*	-1.7403*
	0.25138	0.24726	0.17776	0.15379	0.13325	0.13275	0.14818
Constant	4.05561*	5.60577*	6.71468*	7.06527*	7.14858*	7.39435*	7.62444*
	0.26571	0.25598	0.18331	0.15937	0.13946	0.13236	0.14998
Sample size	859	1330	2232	3133	3664	3601	2762
F-test	79.09	83.3	183.86	211.46	243.05	233.81	151.91
R-squared	0.4826	0.3871	0.4529	0.4038	0.3995	0.3944	0.3558
Adj R-squared	0.4765	0.3824	0.4504	0.4019	0.3979	0.3927	0.3534

Tables 5a: Coefficients of earnings equation, correcting for endogeneity bias: Men, Cor(S, u) = - .2

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
race2	-0.366	-0.294	-0.233	-0.233	-0.174	-0.133	-0.240
race3	-0.066	0.386	0.741	0.741	0.224	0.164	-0.240
race4	-0.225	-0.268	-0.169	-0.169	-0.103	-0.121	-0.147
mpysch	0.006	0.006	0.015	0.015	0.004	0.014	0.013
dpysch	0.008	0.005	0.011	0.011	0.002	-0.001	0.007
reg1	-0.061	-0.051	-0.146	-0.146	-0.179	-0.146	-0.169
reg2	-0.300	-0.264	-0.332	-0.332	-0.334	-0.395	-0.382
reg4	-0.218	-0.097	-0.136	-0.136	-0.118	-0.127	-0.148
reg5	-0.096	-0.055	-0.024	-0.024	-0.049	-0.100	-0.076
yschl	0.160	0.155	0.154	0.154	0.150	0.149	0.139
migrm	0.034	0.208	0.120	0.120	0.084	0.099	0.113
agric	-0.210	-0.220	-0.223	-0.223	-0.332	-0.141	-0.151
_cons	5.423	5.385	5.434	5.434	5.330	5.176	5.173

Table 5.b. Coefficients of earnings equation, correcting for endogeneity bias: Women, Cor(S, u) = - .1

	b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
race2	0.006	0.077	0.096	-0.071	-0.057	-0.096	0.076
race3	-0.305	-0.258	-0.218	0.392	0.072	0.150	-0.053
race4	0.202	-0.021	-0.014	-0.112	-0.036	-0.045	0.044
mpysch	-0.205	-0.055	-0.028	-0.024	-0.007	0.000	-0.023
dpysch	0.000	-0.004	-0.001	-0.009	0.001	-0.010	-0.007
reg1	-0.358	0.018	-0.097	-0.085	-0.150	-0.051	-0.146
reg2	-0.482	-0.335	-0.382	-0.367	-0.416	-0.338	-0.337
reg4	-0.234	0.024	0.024	-0.076	-0.037	-0.009	0.020
reg5	-0.210	0.089	-0.059	-0.134	-0.069	-0.060	-0.183
yschl	0.374	0.244	0.217	0.207	0.212	0.207	0.242
migrm	0.412	0.144	0.147	0.140	0.181	0.138	0.214
agric	0.614	0.005	0.121	0.346	0.327	0.202	0.519
_cons	3.044	3.723	4.088	4.259	3.910	3.993	3.734

Table 6a Contribution of schooling and parental education opportunities to inequality of individual earnings: 5-year cohorts

(Using earning equation without parental education)

		b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
MEN								
Total Inequality	Gini	0.586	0.606	0.579	0.547	0.526	0.509	0.47
	Theil	*0.663*	*0.785*	*0.644*	*0.557*	*0.527*	*0.497*	*0.42*
Schooling as fully circumstance								
(i) Equalizing years of schooling	Gini	0.452	0.468	0.45	0.436	0.426	0.41	0.409
	Theil	*0.377*	*0.426*	*0.389*	*0.363*	*0.367*	*0.32*	*0.334*
(ii) Setting a lower bound of 8 years of education	Gini	0.485	0.514	0.493	0.476	0.467	0.451	0.426
	Theil	*0.431*	*0.541*	*0.459*	*0.42*	*0.424*	*0.392*	*0.353*
(iii) Replacing by 1966-70 cohort distribution	Gini	0.584	0.594	0.598	0.563	0.551	0.549	
	Theil	*0.644*	*0.707*	*0.792*	*0.613*	*0.607*	*0.574*	
(iv) = (ii) + (iii)	Gini	0.477	0.501	0.5	0.467	0.457	0.445	0.426
	Theil	*0.423*	*0.5*	*0.558*	*0.423*	*0.425*	*0.381*	*0.353*
Schooling as circumstance only through parental education								
(v) Equalizing parental education	Gini	0.515	0.524	0.511	0.483	0.462	0.44	0.439
	Theil	*0.489*	*0.519*	*0.501*	*0.437*	*0.426*	*0.361*	*0.401*
(vi) Setting a lower bound of 6 years of education	Gini	0.539	0.552	0.55	0.51	0.49	0.482	0.461
	Theil	*0.55*	*0.616*	*0.617*	*0.502*	*0.482*	*0.453*	*0.442*
(vii) Replacing by 1966-70 cohort distribution	Gini	0.539	0.556	0.568	0.526	0.514	0.504	
	Theil	*0.53*	*0.609*	*0.754*	*0.538*	*0.547*	*0.49*	
(viii) = (vii) + (vi)	Gini	0.499	0.52	0.535	0.49	0.478	0.467	0.461
	Theil	*0.455*	*0.533*	*0.677*	*0.473*	*0.484*	*0.426*	*0.442*

Table 6a (cont(d). Contribution of schooling and parental education opportunities to inequality of individual earnings: 5-year cohorts
(Using earning equation without parental education)

		b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
WOMEN								
Total Inequality	Gini	0.597	0.563	0.601	0.586	0.567	0.545	0.518
	Theil	*0.801*	*0.639*	*0.778*	*0.692*	*0.625*	*0.565*	*0.509*
Schooling as fully circumstance								
(i) Equalizing years of schooling	Gini	0.486	0.43	0.449	0.45	0.449	0.447	0.409
	Theil	*0.484*	*0.35*	*0.393*	*0.419*	*0.38*	*0.389*	*0.311*
(ii) Setting a lower bound of 8 years of education	Gini	0.512	0.472	0.506	0.513	0.5	0.483	0.463
	Theil	*0.551*	*0.437*	*0.538*	*0.536*	*0.477*	*0.44*	*0.403*
(iii) Replacing by 1966-70 cohort distribution	Gini	0.596	0.575	0.59	0.58	0.6	0.614	
	Theil	*0.75*	*0.687*	*0.695*	*0.725*	*0.736*	*0.74*	
(iv) = (ii) + (iii)	Gini	0.506	0.473	0.486	0.489	0.498	0.495	0.463
	Theil	*0.533*	*0.461*	*0.47*	*0.52*	*0.5*	*0.485*	*0.403*
Schooling as circumstance only through parental education								
(v) Equalizing parental education	Gini	0.53	0.479	0.504	0.508	0.5	0.491	0.442
	Theil	*0.601*	*0.436*	*0.492*	*0.527*	*0.504*	*0.481*	*0.385*
(vi) Setting a lower bound of 6 years of education	Gini	0.552	0.523	0.545	0.544	0.543	0.542	0.485
	Theil	*0.643*	*0.569*	*0.642*	*0.632*	*0.641*	*0.612*	*0.469*
(vii) Replacing by 1966-70 cohort distribution	Gini	0.559	0.593	0.576	0.581	0.577	0.566	
	Theil	*0.653*	*0.768*	*0.647*	*0.744*	*0.694*	*0.634*	
(viii) = (vii) + (vi)	Gini	0.523	0.542	0.528	0.542	0.537	0.528	0.485
	Theil	*0.575*	*0.644*	*0.545*	*0.658*	*0.607*	*0.558*	*0.469*

Table 6b Contribution of schooling and parental education opportunities to inequality of individual earnings: 5-year cohorts

(Using earning equation with schooling and parental education)

		b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
MEN								
Total Inequality	Gini	0.588	0.619	0.582	0.545	0.528	0.514	0.475
	Theil	*0.655*	*0.821*	*0.643*	*0.544*	*0.528*	*0.505*	*0.429*
Schooling as fully circumstance								
(i) Equalizing years of schooling and parental education in earning equation	Gini	0.451	0.469	0.443	0.429	0.417	0.397	0.395
	Theil	*0.368*	*0.427*	*0.372*	*0.345*	*0.349*	*0.297*	*0.307*
(ii) Setting lower bounds (8 years for schooling, 6 years for parental education)	Gini	0.489	0.526	0.495	0.476	0.467	0.453	0.427
	Theil	*0.432*	*0.567*	*0.456*	*0.412*	*0.419*	*0.391*	*0.351*
(iii) Replacing by 1966-70 cohort distributions	Gini	0.534	0.558	0.541	0.506	0.493	0.478	
	Theil	*0.513*	*0.629*	*0.595*	*0.479*	*0.475*	*0.429*	
(iv) = (ii) + (iii)	Gini	0.481	0.51	0.502	0.462	0.45	0.431	0.427
	Theil	*0.418*	*0.521*	*0.564*	*0.409*	*0.405*	*0.35*	*0.351*
Schooling as circumstance only through parental education								
(v) Equalizing parental education in eanring and schooling equations	Gini	0.504	0.533	0.494	0.464	0.448	0.421	0.427
	Theil	*0.455*	*0.546*	*0.455*	*0.392*	*0.393*	*0.324*	*0.371*
(vi) Setting lower bounds (6 years for parental education)	Gini	0.525	0.561	0.53	0.489	0.473	0.456	0.449
	Theil	*0.502*	*0.639*	*0.551*	*0.444*	*0.437*	*0.396*	*0.409*
(vii) Replacing by 1966-70 cohort distributions	Gini	0.548	0.571	0.57	0.521	0.508	0.495	0.489
	Theil	*0.538*	*0.651*	*0.739*	*0.514*	*0.521*	*0.463*	*0.465*
(viii) = (vii) + (vi)	Gini	0.506	0.534	0.534	0.485	0.473	0.459	0.455
	Theil	*0.458*	*0.573*	*0.66*	*0.45*	*0.46*	*0.402*	*0.407*
Schooling as pure effort								
(ix) Equalizing parental education in earning equation	Gini	0.517	0.537	0.514	0.481	0.464	0.445	0.444
	Theil	*0.481*	*0.555*	*0.5*	*0.424*	*0.427*	*0.369*	*0.41*

Table 6b (cont(d). Contribution of schooling and parental education opportunities to inequality of individual earnings: 5-year cohorts

(Using earning equation with schooling and parental education)

		b1936_40	b1941_45	b1946_50	b1951_55	b1956_60	b1961_65	b1966_70
WOMEN								
Total Inequality	Gini	0.608	0.57	0.609	0.586	0.569	0.546	0.523
	Theil	*0.827*	*0.653*	*0.799*	*0.693*	*0.62*	*0.549*	*0.509*
Schooling as fully circumstance								
(i) Equalizing years of schooling and parental education in earning equation	Gini	0.501	0.431	0.461	0.463	0.452	0.444	0.417
	Theil	*0.529*	*0.35*	0.433	*0.448*	*0.386*	*0.358*	*0.321*
(ii) Setting lower bounds (8 years for schooling, 6 years for parental education)	Gini	0.515	0.469	0.511	0.516	0.494	0.48	0.461
	Theil	*0.56*	*0.427*	*0.551*	*0.539*	*0.46*	*0.419*	*0.395*
(iii) Replacing by 1966-70 cohort distributions	Gini	0.562	0.535	0.551	0.545	0.543	0.522	
	Theil	*0.674*	*0.588*	*0.613*	*0.63*	*0.58*	*0.508*	
(iv) = (ii) + (iii)	Gini	0.511	0.478	0.493	0.497	0.493	0.47	0.44
	Theil	*0.548*	*0.482*	*0.485*	*0.542*	*0.483*	*0.424*	*0.354*
Schooling as circumstance only through parental education								
(v) Equalizing parental education in earnng and schooling equations	Gini	0.52	0.454	0.485	0.493	0.473	0.456	0.419
	Theil	*0.588*	*0.384*	*0.454*	*0.497*	*0.428*	*0.382*	*0.329*
(vi) Setting lower bounds (6 years for parental education)	Gini	0.537	0.493	0.52	0.526	0.508	0.505	0.456
	Theil	*0.605*	*0.488*	*0.566*	*0.583*	*0.519*	*0.489*	*0.394*
(vii) Replacing by 1966-70 cohort distributions	Gini	0.575	0.601	0.579	0.576	0.566	0.551	0.504
	Theil	*0.696*	*0.785*	*0.653*	*0.73*	*0.64*	*0.576*	*0.463*
(viii) = (vii) + (vi)	Gini	0.535	0.55	0.53	0.537	0.526	0.513	0.473
	Theil	*0.609*	*0.661*	*0.55*	*0.645*	*0.557*	*0.503*	*0.413*
Schooling as pure effort								
(viii) Equalizing parental education in earning equation	Gini	0.541	0.486	0.512	0.508	0.502	0.492	0.447
	Theil	*0.627*	*0.45*	*0.513*	*0.528*	*0.499*	*0.465*	*0.385*

Table 7a:Intergenerational Educational Mobility: cohort 1936-1940

Parental years of schooling, measured as deviations from the mean	Individuals' years of schooling, measured as deviations from the mean					
	-2 or less'	'Between -1 and -2'	Between –1 and 1'	Between 1 and 2'	2 or more'	Total
	89.03	3.57	1.31	2.5	3.59	*100*
-2 or less'	37.06	1.49	0.55	1.04	1.49	*41.62*
	80.28	6.57	2.84	5.33	4.97	*100*
'Between -1 and -2'	11.3	0.92	0.4	0.75	0.7	*14.07*
	60.75	6.74	4.62	9.14	18.75	*100*
Between -1 and 1'	14.85	1.65	1.13	2.23	4.58	*24.45*
	37.57	7.67	6.62	11.2	36.94	*100*
Between 1 and 2'	3.85	0.78	0.68	1.15	3.78	*10.23*
	10.7	4.58	4.03	13.73	66.96	*100*
2 or more'	1.03	0.44	0.39	1.32	6.44	*9.62*
Total	*68.08*	*5.29*	*3.14*	*6.49*	*17*	*100*

Table 7b: Intergenerational Educational Mobility: cohort 1946-1950

Parental years of schooling, measured as deviations from the mean	Individuals' years of schooling, measured as deviations from the mean					
	-2 or less'	'Between -1 and -2'	Between -1 and 1'	Between 1 and 2'	2 or more'	Total
	80.62	4.86	2.33	5.48	6.71	*100*
-2 or less'	26.62	1.61	0.77	1.81	2.22	*33.02*
	67.47	7.52	4.45	7.09	13.47	*100*
'Between -1 and -2'	10.17	1.13	0.67	1.07	2.03	*15.07*
	48.89	8.38	5.29	10.46	26.98	*100*
Between -1 and 1'	13.53	2.32	1.46	2.89	7.46	*27.66*
	23.52	6.4	4.11	13.19	52.78	*100*
Between 1 and 2'	2.78	0.75	0.48	1.56	6.23	*11.8*
	5.78	2.1	3.36	7.92	80.84	*100*
2 or more'	0.72	0.26	0.42	0.99	10.06	*12.44*
Total	*53.81*	*6.07*	*3.8*	*8.31*	*28*	*100*

Table 7c: Intergenerational Educational Mobility: cohort 1956-1960

Parental years of schooling, measured as deviations from the mean	Individuals' years of schooling, measured as deviations from the mean					
	-2 or less'	'Between -1 and -2'	Between -1 and 1'	Between 1 and 2'	2 or more'	Total
	68.64	6.91	6.94	8.3	9.21	*100*
-2 or less'	17.06	1.72	1.73	2.06	2.29	*24.86*
	53.11	8.91	11.07	10.47	16.43	*100*
'Between -1 and -2'	7.66	1.29	1.6	1.51	2.37	*14.43*
	31.95	8.54	10.94	15.02	33.55	*100*
Between -1 and 1'	9.57	2.56	3.28	4.5	10.05	*29.96*
	15.11	5.03	7.44	14.87	57.55	*100*
Between 1 and 2'	2.16	0.72	1.06	2.12	8.22	*14.27*
	5.6	1.81	3.97	7.68	80.93	*100*
2 or more'	0.92	0.3	0.65	1.27	13.34	*16.48*
Total	*37.37*	*6.58*	*8.32*	*11.46*	*36.27*	*100*

Table 7d: Intergenerational Educational Mobility: cohort 1966-1970

Parental years of schooling, measured as deviations from the mean	Individuals' years of schooling, measured as deviations from the mean					
	-2 or less'	'Between -1 and -2'	Between -1 and 1'	Between 1 and 2'	2 or more'	Total
	55.49	9.76	13.1	8.97	12.68	*100*
-2 or less'	11.2	1.97	2.64	1.81	2.56	*20.18*
	42.02	11.15	16.54	14.02	16.27	*100*
'Between -1 and -2'	6.17	1.64	2.43	2.06	2.39	*14.67*
	23.41	10.94	15.06	18.17	32.42	*100*
Between -1 and 1'	7.34	3.43	4.72	5.69	10.16	*31.34*
	12.34	7.19	12.16	18.28	50.03	*100*
Between 1 and 2'	1.8	1.05	1.77	2.66	7.29	*14.56*
	4.67	3.43	6	10.88	75.01	*100*
2 or more'	0.9	0.66	1.16	2.1	14.44	*19.25*
Total	*27.39*	*8.74*	*12.72*	*14.32*	*36.83*	*100*