Schooling Inequality, Returns to Schooling, and Earnings Inequality: Evidence from Brazil and South Africa

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Abstract

Human capital models imply that both the distribution of education and returns to education affect earnings inequality. Decomposition of these "quantity" and "price" components have been important in understanding changes in earnings inequality. Most previous literature does not consider the case in which returns to schooling differ by schooling level. We show theoretically that increases in returns to schooling at low levels of schooling tend to be equalizing, while increases in returns to high levels of schooling tend to be disequalizing. We apply these analytical results to Brazil and South Africa. Both countries have high earnings inequality, and both have experienced changes in returns to schooling that differ by schooling level. While both countries have had declines in schooling inequality, only Brazil has translated those into declines in earnings inequality. In South Africa, rising returns to schooling at the top have offset equalizing changes in the schooling distribution.

Introduction

The link between education and the distribution of income has long been fundamental to research on inequality. Theoretical models and vast empirical evidence point to a large explanatory role for education in the distribution of income, especially the distribution of labor earnings. Standard human capital models imply that both the distribution of education and the returns to education will affect earnings inequality. Decomposition of these two components, often referred to as the "quantity" and "price" components, have played an important role in understanding changes in earnings inequality in both high-income countries and developing countries (e.g. Juhn, Murphy, Pierce 1993, for the United States, and World Bank 2011 for Latin America).

The goal of this paper is to advance our understanding of both the theory and the empirical evidence regarding the interactions of schooling inequality, returns to schooling and earnings inequality. We focus on two main questions. First, what is the relationship between inequality in schooling and inequality in earnings? As shown by Lam and Levison (1992), it is theoretically possible to generate increases in earnings inequality by expansions of schooling that decrease schooling inequality. This phenomenon of declining inequality in schooling associated with rising inequality in earnings seems to have been the case for Brazil and may actually be quite common during the early stages of economic development. Improvements in the schooling distribution appear to eventually become equalizing, however. We elaborate on these issues from a theoretical perspective below, and discuss how they apply empirically to the cases of Brazil and South Africa.

The second issue we consider is how changes in returns to schooling affect earnings inequality when returns differ by the level of schooling. What happens, for example, if the returns to completing grade 8 increase while returns to all other grades remain constant? A common feature of labor markets in developing countries has been for returns to schooling to change at different rates (and even in different directions) at different levels of schooling. Returns to university may have increased, for example, at the same time that returns to secondary schooling declined. In this context it can be misleading to generalize about whether the change in average returns to schooling has been equalizing or disequalizing. As we will show, and as intuitively makes sense, increases in returns to schooling at low grades may actually be inequality reducing, while increases in returns to schooling at high grades are inequality increasing. We develop a general framework for analyzing these issues, and derive some simple analytical results about the impact of returns to schooling at different levels of schooling on earnings inequality.

These results provide a useful framework for empirical analysis. They call attention to an interesting summary statistic that has not previously been studied – the year of schooling at which mean log earnings is earned. Our analytical results demonstrate that increases in returns to schooling above this level will be disequalizing, while increases in returns below this level will be equalizing. This level of schooling also provides a benchmark for understanding how changes in the distribution of schooling affect earnings inequality. Changes in the schooling distribution that shift the distribution toward the schooling level of mean log earnings will be equalizing, while shifts away from that schooling level (in either direction) will be disequalizing.

We use this framework to guide empirical analysis of schooling inequality, returns to schooling, and earnings inequality in Brazil and South Africa in recent decades. These two countries competed for many years for the dubious distinction of being the most unequal country in the world. Brazil has experienced declining inequality in recent years, however, while South Africa has experienced persistently high inequality. Both countries have excellent microdata that make it possible to look closely at the distribution of schooling and the distribution of earnings. In Brazil we are able to track both distributions from 1976 to the present using the annual labor market survey. In South Africa we have a consistent labor market series from 1994 to the present.

This preliminary draft presents some of our key theoretical results. We then present some examples of empirical analysis that is guided by the theoretical results. In the final paper we will use counterfactual simulations to look at how changes in schooling distributions and returns to schooling can explain the changes in earnings inequality in the two countries.

Theoretical Links Between Schooling Inequality and Earnings Inequality

We begin our theoretical analysis with a simplified version of the standard human capital earnings equation. Leaving experience and other determinants of earnings aside for now, the logarithm of the *i*th worker's earnings can be expressed as

$$\log Y_i = \alpha + \beta S_i + u_i \quad (1)$$

where y_i is earnings, S_i is years of schooling, and u_i is a residual uncorrelated with schooling. Given Equation (1), the variance of log earnings, a standard mean-invariant measure of wage inequality, is

$$V(\log Y) = \beta^2 V(S) + V(u) \quad (2)$$

where V denotes variance. This simple result demonstrates an important point about the link between schooling inequality and earnings inequality. If the relationship between schooling and earnings is log-linear as in (1), then earnings inequality (as measured by the log variance) is a linear function of the variance in schooling. This has a number of important implications that are often neglected in discussions of the link between the distribution of schooling and the distribution of earnings. Suppose, for example, that we could double the schooling of every worker, holding returns to schooling constant. This would quadruple the variance in years of schooling and thus quadruple the "explained" component of earnings inequality. If we measure inequality in schooling by some standard mean-invariant measure of inequality, this doubling of schooling would imply no change in schooling inequality. Alternatively, giving each worker one additional year of schooling would unambiguously reduce schooling inequality, but would have no effect on earnings inequality.

Lorenz dominance in schooling distributions and earnings distributions

In order to look at the relationship between schooling inequality and earnings inequality in a fairly general way, consider a linear transformation of the schooling distribution, mapping some initial distribution S' into a new distribution S'',

$$S_i'' = \gamma + \delta S_i' . \quad (3)$$

Even with simple transformations such as Equation (3), we can generate changes in the schooling distribution that imply unambiguous reductions in schooling inequality and unambiguous *increases* in earnings inequality, using the criterion of Lorenz dominance.

> ***Proposition 1:*** Given the earnings generation process in Equation (1) and the linear transformation of the schooling distribution in Equation (3), any transformation in which $\gamma > 0$ and $\delta > 1$ will cause the schooling distribution to become unambiguously more equal and the earning distribution to become unambiguously less equal, in the sense that S'' Lorenz dominates S' and Y' Lorenz dominates Y''.

To prove Proposition 1, it is useful to observe that we will have Lorenz dominance whenever the proportional difference in the schooling (or earnings) of any two randomly drawn individuals in the distribution is smaller in the Lorenz dominating distribution. That is,

$$S'' \text{ Lorenz dominates } S' \text{ if } \frac{S''_j}{S''_i} < \frac{S'_j}{S'_i}, \forall(i, j) \text{ s.t. } S'_j > S'_i \tag{4}$$

Given the transformation in Equation (3), the change in the ratios of any two schooling levels is

$$\frac{S''_j}{S''_i} - \frac{S'_j}{S'_i} = \frac{\gamma + \delta S'_j}{\gamma + \delta S'_i} - \frac{S'_j}{S'_i} \tag{5}$$

Inspection of Equation (5) indicates that the difference will be negative for any $\gamma > 0$, with the value of δ affecting the magnitude but not the sign of the difference for any $\delta > 0$. This implies that

$$S'' \text{ Lorenz dominates } S' \text{ for any } \gamma > 0 \text{ and } \delta > 0 \tag{6}$$

Turning to the earnings distribution, it is useful to begin by pointing out the simple special case is of an additive shift in schooling such that $\gamma > 0$ and $\delta = 1$ (for example, giving every person one additional year of schooling). This implies an unambiguous reduction in the inequality of schooling by the criterion of Lorenz dominance. Since this leaves the variance of schooling unchanged, however, it is clear from Equation (2) that the variance in log earnings will be unchanged. This lack of change in earnings inequality is not limited to the log variance measure. Since an additive increase in schooling will cause a multiplicative increase in each person's income, any measure of inequality will be unaffected. Put another way, the additive shift in schooling implies an additive shift in the logarithm of earnings, which is equivalent to simply multiplying the earnings distribution by a constant, a shift that would leave all measures of earnings inequality unchanged. Another simple illustrative case is a multiplicative transformation in schooling, with $\gamma = 0$ and $\delta > 1$ (for example, increasing every individual's schooling by 10 percent). This will have no effect on inequality in schooling, with the Lorenz curves identical for S' and S''. It will increase the variance of schooling by δ^2, however, so the log variance of earnings will increase. Once again, the result is much more general than the log variance. In order to see this, it is useful to move to the general case in which $\gamma \neq 0$ and $\delta \neq 1$, comparing inequality in earnings before and after the change in schooling.

Following the approach above, consider the ratio of earnings for two individuals in each of the two schooling distributions. Consider two individuals *i* and *j* with initial schooling levels $S_j' > S_i'$ and income levels $Y_j' > Y_i'$. If the earnings ratio Y_j / Y_i increases when schooling is changed from S' to S'', for all possible pairings *i* and *j*, then the new earnings distribution will be unambiguously less equal by the criterion of Lorenz dominance. That is,

$$Y' \text{ Lorenz dominates } Y'' \text{ if } \frac{Y_j''}{Y_i''} > \frac{Y_j'}{Y_i'}, \forall (i, j) \text{ s.t. } S_j' > S_i' \tag{7}$$

Since the logarithm is a monotonic transformation, we can also express the Lorenz dominance condition as $\log[Y_j''/Y_i''] > \log[Y_j' - Y_i']$. If earnings are generated as in Equation (1), and the schooling transformation is given by Equation (3), the difference in log earnings between *i* and *j* after the tranformation (assuming that the return to schooling β and the residuals u_i and u_j remain constant) is

$$\begin{aligned} \log Y_j'' - \log Y_i'' &= \alpha + \beta(\gamma + \delta S_j') + u_j - [\alpha + \beta(\gamma + \delta S_i') + u_i] \\ &= \beta\delta(S_j' - S_i') + u_j - u_i \end{aligned} \tag{8}$$

The difference in log earnings before the transformation will be $\beta(S_j' - S_i') + (u_j - u_i)$, so the change in the difference in log earnings will be $\beta(S_j' - S_i')(\delta - 1)$. Using the condition in Equation (7), this implies that

$$Y' \text{ Lorenz dominates } Y'' \text{ if } \delta > 1 \tag{9}$$

This holds for all values of γ. Combining the results in Equation (6) and Equation (9) gives the result in Proposition 1.

Proposition 1 was derived assuming the log-linear relationship between schooling and earnings of Equation (1). While this is a very standard assumption, with strong empirical support, it is important to note that similar results will exist whenever there is a convex relationship between schooling and earnings. It is the convexity in general, not the specific exponential relationship, that leads to the result that an unambiguous reduction in schooling inequality can lead to an unambiguous increase in earnings inequality. The linear transformation in schooling is used simply for analytical simplicity. Obviously if we can generate distributions in schooling that have opposite effects on schooling inequality and earnings inequality using these simple linear transforms, we can do the same with much more general transformations of the schooling distribution.

Opposing trends in schooling inequality and income inequality are far from being just a theoretical possibility. They may be fairly common in the process of economic development. Brazil's experience, for example, is consistent with a pattern in which improvements in schooling inequality coincided with increases in income inequality. As shown by Lam and Levison (1992), the trend across cohorts in Brazil for cohorts born between 1925 and 1950 was for mean schooling to rise at a slightly faster rate than the standard deviation. Schooling inequality was thus declining over this period, as measured by the coefficient of variation and as indicated by constantly improving Lorenz curves for schooling. Since the variance of schooling was rising, however, these improvements in schooling inequality did not translate into improvements in earnings inequality. The "explained variance" in the log variance of earnings, $\beta^2 V(S)$, rose steadily across cohorts, helping contribute to continued high inequality in Brazil. As shown below, the variance of schooling has peaked among more recent cohorts in Brazil, suggesting that this component could contribute to reductions in earnings inequality in the future.[1]

While there is intuitive appeal to the notion that a more equal distribution of schooling should lead to a more equal distribution of earnings, there is clearly no theoretical reason to expect such a relationship to hold. What might be considered unambiguous improvements in the distribution of schooling (as indicated, for example, by stochastic dominance), could plausibly lead to increased inequality in earnings. The fundamental reason for this is that earnings are very likely to be a convex function of schooling, the simple log-linear wage equation being just one simple example of such convexity. Any convex relationship between schooling and earnings will tend to produce the result that proportional increases in schooling will increase earnings inequality. This point will be important in analyzing the link between schooling inequality and earnings inequality in Brazil and South Africa.

[1] Ram (1990) shows with cross-national data that the standard deviation of schooling tends to follow an inverted-U pattern in relation to mean schooling, with a peak when the mean is around seven years.

Generalizing the relationship between schooling and earnings

The results above assume that there is a single rate of return to schooling that applies to all levels of schooling. One of the important recent patterns in returns to schooling in developing countries, however, is the emergence of convex returns to schooling, with returns increasing at higher levels of schooling (especially post-secondary) at the same time that they have fallen at intermediate levels of schooling.

This pattern complicates what we mean when we consider the relationship between returns to schooling and earnings inequality. What happens to inequality if, for example, we increase the return to grade 8, holding returns at other grades constant. What if we increase returns to grade 4 or grade 12? This section provides an analytical way to answer to these questions.

Consider a very general model of the relationship between schooling and earnings.

$$y_i \equiv \log Y_i = \alpha + \sum_j \beta_j S_{ji} + u_i \tag{10}$$

where Y_i is earnings, y_i is the log of earnings S_{ji} is a 0,1 indicator for whether person *i* in the *j*th schooling category (which could be single years of schooling in the most general case, but could also be larger categories), and u_i is a residual uncorrelated with schooling.[2] Denote mean log earnings as $\overline{y}$ and mean log earnings for schooling level j as $\overline{y}_j$. The following proposition describes the relationship between

> ***Proposition 2:*** If $\hat{s}$ is a level of schooling for which $\ln \overline{y}_j > \overline{y}, \forall j > \hat{s}$ and $\overline{y}_j < \overline{y}, \forall j < \hat{s}$, then increases in β_j for $j > \hat{s}$ will increase the variance of log earnings, and increases in in β_j for $j < \hat{s}$ will increase the variance of log earnings.

To prove Proposition 2, note that the variance of log earnings for this more general model can be written as:

$$V(\log y) = \sum_j \beta_j^2 V(S_j) - 2\sum_j \sum_{k \neq j} \beta_j \beta_k p_j p_k + V(u), \tag{11}$$

where p_j is the proportion in schooling category *j*. Since the S_j. terms only take on values of 0 or 1, $V(S_j)=p_j(1-p_j)$. What happens to inequality if we increase one of the β terms? This is still an increase in returns to schooling, but is only an increase for one category of schooling (relative to

[2] Note that nothing about this analysis requires that these be schooling categories. The same results would apply to any other categories, such as age, region, or gender.

some arbitrary omitted category) and no longer translates necessarily into an increase in inequality. We take the derivative of Equation (11) with respect to β_1, which could arbitrarily be assigned to any schooling category and thus is completely general:

$$\frac{\partial V(\log Y)}{\partial \beta_1} = 2\beta_1 p_1 - 2\beta_1 p_1^2 - 2p_1 \sum_{j \neq 1} \beta_j p_j = 2p_1 \left[\beta_1 - \beta_1 p_1 - \sum_{j \neq 1} \beta_j p_j \right], \qquad (12)$$

Note that $\beta_1 p_1 + \sum_{j \neq 1} \beta_j p_j = \bar{y} - \alpha$, where $\bar{y} = E(\log y)$, and $\alpha + \beta_1 = \bar{y}_1$, where $\bar{y}_1 = E(\log y | S_1 = 1)$. Substituting into (12), the result simplifies to:

$$\frac{\partial V(\log y)}{\partial \beta_1} = 2p_1 \left[\bar{y}_1 - \bar{y} \right], \qquad (13)$$

or

$$dV(\log y) = d\beta_1 * 2p_1 \left[\bar{y}_1 - \bar{y} \right]. \qquad (14)$$

The result is very intuitive. Increasing β_1 will increase the earnings of the first schooling category (arbitrarily defined) relative to the omitted category, and therefore relative to every other category as well. This will be equalizing if the first category had a mean below the overall mean and will be disequalizing if its mean were above the overall mean. The magnitude of the change will depend on how far the group's mean is above or below the overall mean, and on the relative size of the group. For example, if the group's mean of log earnings were 0.1 below the overall log mean (in other words, a difference of approximately 10%), and if the group were 10% of the income earning population, an increase in β_1 by 0.01 would reduce the variance of log earnings by 2*0.1*0.1*0.01=0.0002.

If we calculate this derivative for every single year of schooling, Equation (14) calls attention to a statistic that we do not ordinarily calculate – the year of schooling for which mean log earnings is equal (or closest to equal) to overall mean log earnings. Suppose there is a level of schooling $\hat{s}$ such that $\bar{y}_i > \bar{y}, \forall i > \hat{s}$ and $\bar{y}_i < \bar{y}, \forall i < \hat{s}$. Then increasing returns to schooling for all years below $\hat{s}$ is equalizing, and increasing returns for years above $\hat{s}$ is disequalizing. This is the result in Proposition 2.

It is also interesting to consider whether the year of schooling at which mean log earnings is reached is less than or greater than mean years of schooling. That is, is $\hat{s} - \bar{s}$ positive, negative, or zero? It is easy to see that in the simple linear Mincer earnings equation, $\hat{s} = \bar{s}$, since mean log earnings will be earned by someone with mean schooling, abstracting from other variables such as age and experience. More generally, however, $\hat{s}$ could be greater or less than $\bar{s}$, depending on whether returns to schooling are concave or convex in schooling. If returns are convex, as they have been in South Africa and in many other developing countries in recent years, then $\hat{s} > \bar{s}$ -- the year of schooling associated with mean log earnings is above mean schooling. This means that an increase in returns to schooling will be equalizing even for some years above mean schooling. We look at this empirically below for Brazil and South Africa.

Another interesting question is what happens when we change the distribution of schooling. One simple way to model this is to imagine shifting people from some arbitrary group 2 to some arbitrary group 1, so that $dp_2 = -dp_1$, or, equivalently, $\partial p_2 / \partial p_1 = -1$

$$
\begin{aligned}
\frac{\partial V(\log Y)}{\partial p_1} &= \beta_1^2 - 2\beta_1^2 p_1 + \left(\beta_2^2 - 2\beta_2^2 p_2\right)\frac{\partial p_2}{\partial p_1} - 2\beta_1 \sum_{j\neq 1} \beta_j p_j - 2\beta_2 \sum_{j\neq 2} \beta_j p_j \frac{\partial p_2}{\partial p_1} \\
&= \left(\beta_1 + \alpha\right)^2 - 2\beta_1 \bar{y} - \left(\beta_2 + \alpha\right)^2 + 2\beta_2 \bar{y} \\
&= \bar{y}_1^2 - 2\beta_1 \bar{y} - \bar{y}_2^2 + 2\beta_2 \bar{y} \\
&= \left(\bar{y}_1 - \bar{y}\right)^2 - \left(\bar{y}_2 - \bar{y}\right)^2
\end{aligned}
\quad , \qquad (15)
$$

The result is once again very intuitive. Shifting the population from one group to another will be disequalizing if the second group has mean log earnings that are farther from the mean (in absolute value) than the first group. For example, if mean log earnings for group 2 is 0.2 above overall mean log earnings, while mean log earnings for group 1 is 0.1 below the overall mean, then shifting 10% of the population from group 2 to group 1 will change the variance of log earnings by $(0.1^2 - 0.2^2)$*0.1=(0.01-0.04)*0.1= -0.003. As above, an interesting point of reference is the level of schooling corresponding to mean log earnings. The generalization of Equation (15) is that changes in the schooling distribution that push the distribution toward the level of schooling with mean log earnings will tend to be equalizing, while changes in the distribution that push the distribution away from the level of schooling with mean log earnings will tend to be disequalizing. Note that if returns to schooling are convex then the critical level of schooling will be higher than mean schooling.

Note that the result in (15) can be applied to any variance. We have applied it to the variance of log earnings, which is a mean-adjusted measure of inequality. We could use it to talk about inequality in schooling by noting that we will reduce inequality if we reduce the variance while raising the mean. Using the result in (15), we will do this for the distribution of schooling if we shift people upward in the distribution so that we raise the mean while on average moving people closer to the mean.

Other measures of inequality

The results above apply to the variance of log earnings, one measure of inequality. We can also consider what happens to other measures of inequality when the returns to schooling change, continuing to assume that the fundamental relationship between schooling and earnings is given by the flexible log earnings function in Equation (10). One measure that has a simple analytical result is the Generalized Entropy Measure GE(0), which can be written as

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n}\log\left(\frac{\overline{Y}}{Y_i}\right), \tag{16}$$

where $\overline{Y}$ is the mean of earnings (not the mean of log earnings). Taking the derivative with respect to some β_1:

$$\begin{aligned}\frac{\partial GE(0)}{\partial \beta_1} &= \frac{1}{n}\sum_{i=1}^{n}\frac{\partial \log \overline{Y}}{\partial \beta_1} - \frac{1}{n}\sum_{i=1}^{n}\frac{\partial \log Y_i}{\partial \beta_1} \\ &= p_1\frac{\overline{Y}_1}{\overline{Y}} - p_1 \\ &= p_1\left(\frac{\overline{Y}_1}{\overline{Y}} - 1\right)\end{aligned}, \tag{17}$$

where p_1 is, as above, the proportion of the population in schooling group 1. Note that (17) will be positive when $\overline{Y}_1 > \overline{Y}$ and will be negative when $\overline{Y}_1 < \overline{Y}$. That is, if group 1 has mean earnings above (below) the overall mean, then an increase in β_1 will increase (decrease) inequality as measured by GE(0). The interesting difference from the result for the log variance is that the sign now depends on the difference between the group's mean earnings relative to overall mean earnings, whereas the result for the log variance depends on the difference between the group's mean log earnings and the overall mean log earnings. This means that we will also be interested in the level of schooling at which mean earnings is reached. As we will see below, the level of schooling corresponding to mean earnings will typically be higher than the level of schooling corresponding to mean log earnings, given the convex relationship between schooling and earnings.

Empirical Evidence from Brazil and South Africa

In this section we present some preliminary empirical analysis for Brazil and South Africa that builds off the analytical framework discussed above. We begin with an overview of trends in earnings inequality in the two countries. Figure 1 shows the variance of log earnings for the sample of all men and women with positive earnings in Brazil and South Africa for the total period of our samples. Note that the overall level of earnings inequality in South Africa is similar to the level experienced by Brazil before it began to experience a decline in inequality beginning around declining around 1990.

Figure 1 also shows explained variance based on a regression that includes schooling dummies for each year of schooling along with age and age squared. Once again we see that the level of explained variance is fairly similar in the two countries. The R^2 in these earnings regressions is over 0.4, much higher than is typically found in similar earnings regressions in the U.S. (Lam and Levison 1992). The fact that the explained variance closely tracks the decline in earnings inequality in Brazil is important. It means that some combination of the change in the distribution of schooling and the change in returns to schooling account for most of the decline in earnings inequality in Brazil. As we will see, one of the mysteries in South Africa is why declines in inequality in schooling have not translated into similar declines in earnings inequality.

Figure 2 shows some key measures of the distribution of education for the working-age population in the two countries. Both countries have had rapid increases in mean education, but South Africa's mean in 1994 was already higher than Brazil had reached by 2008. The coefficient of variation, a simple mean-adjusted measure of education inequality, is shown on the same scale for both countries, revealing that Brazil had much higher level of education inequality than South Africa in the 1990s. The standard deviation, a key determinant of earnings inequality in the standard human capital earnings equation, has been fairly similar in the two countries, although it has declined more in South Africa than in Brazil.

Figure 3 shows the statistic that we argue is key to understanding the relationship between returns to schooling and earnings inequality – the level of schooling at which mean log earnings is reached. The figure also shows the mean level of schooling for those with positive earnings. Note that in Brazil the level of schooling corresponding to mean log earnings was below the mean level of schooling until around 1985, then increases well above mean schooling in later years. Given our analytical results above, we can see that increases in returns to schooling in the intermediate levels, say around seven years of schooling, would have been disequalizing until the late 1990s, after which they would have been equalizing. The results for South African can be given a similar interpretation.

Figure 4 shows what has happened to returns to schooling in the top, middle, and bottom of the schooling distribution, using cutoffs for each country that reflect key schooling breaks (e.g., Grade 11 is the end of secondary in Brazil, while Grade 12 is the end of secondary in South

Africa). We see several key differences in the patterns for the two countries. South Africa has seen a dramatic increase in returns to grade 12 and above since 1994. Our preliminary simulations indicate that this is the main factor explaining why improvements in schooling inequality have not led to decreases in earnings inequality. At the same time, the declines in returns to grade 9-11 have had a mixed impact. Based on our analytical results and the patterns in Figure 3, we see that declines in returns to grades 9-11 would have been equalizing in th 1990s, but became disequalizing by the mid 2000s.

In contrast, Brazil has had relatively constant returns to the highest levels of education. This has meant that improvements in the distribution of education have been translated into declines in inequality. The declining returns to intermediate levels of schooling are more complicated, as in South Africa. They were equalizing for much of the period, but may have been somewhat disequalizing in more recent years.

Future Plans for the Paper

We have done preliminary counterfactual simulations for South Africa that enable us to decompose the role of changing schooling distributions and changing returns to schooling on changes in inequality. We do these by estimating earnings regressions and using the coefficients for different years to analyze the impact of changing returns to schooling, holding the distribution of schooling constant. These results suggest that rising returns to schooling at the top of the schooling distribution have been disequalizing, offsetting what would have been equalizing improvements in the distribution of education. We will conduct similar counterfactuals for Brazil. We are also in the process of updating the Brazilian data to 2011.

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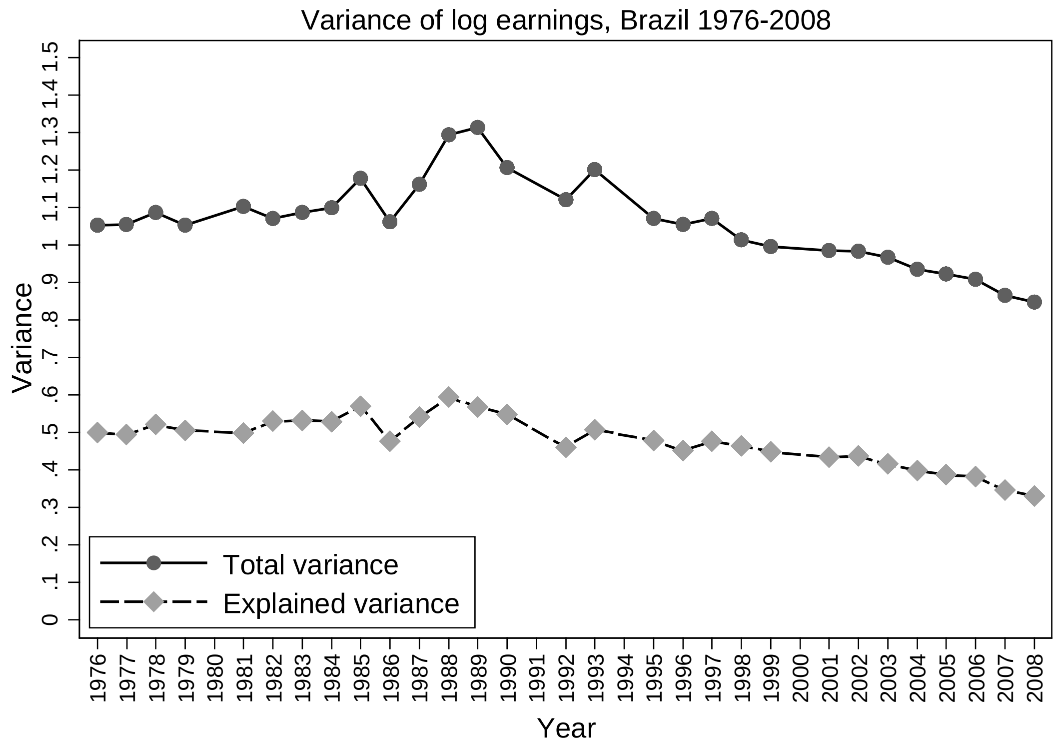
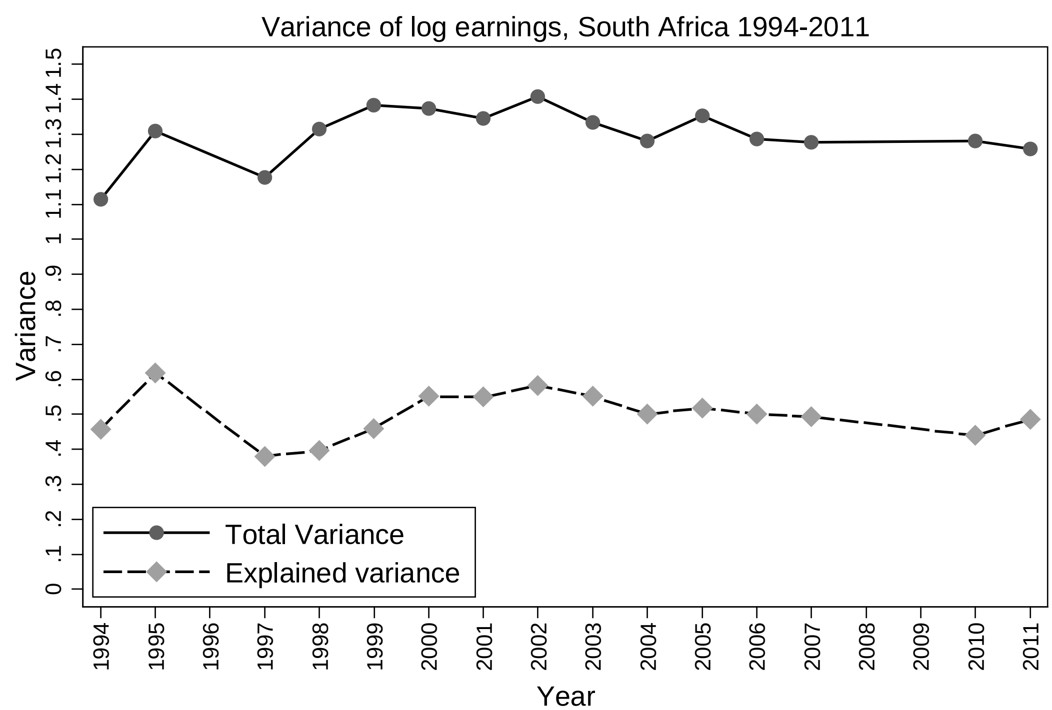
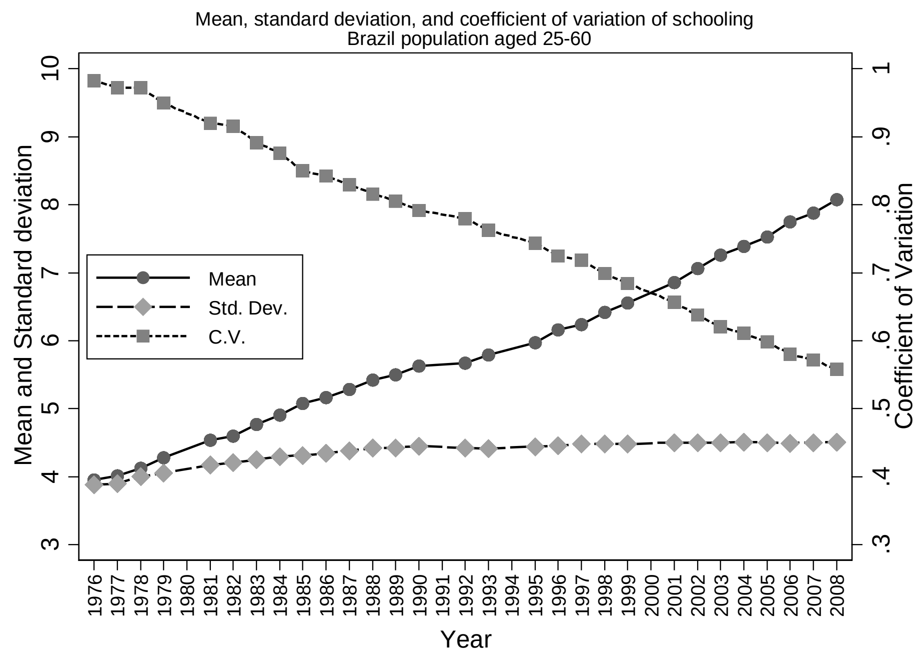
Figure 1. Total and explained variance of log earnings, Brazil and South Africa





Explained variance based on regression with schooling dummies plus age and age squared

Figure 2. Mean, Standard Deviation, and Coefficient of Variation of Years of Education, Brazil and South Africa



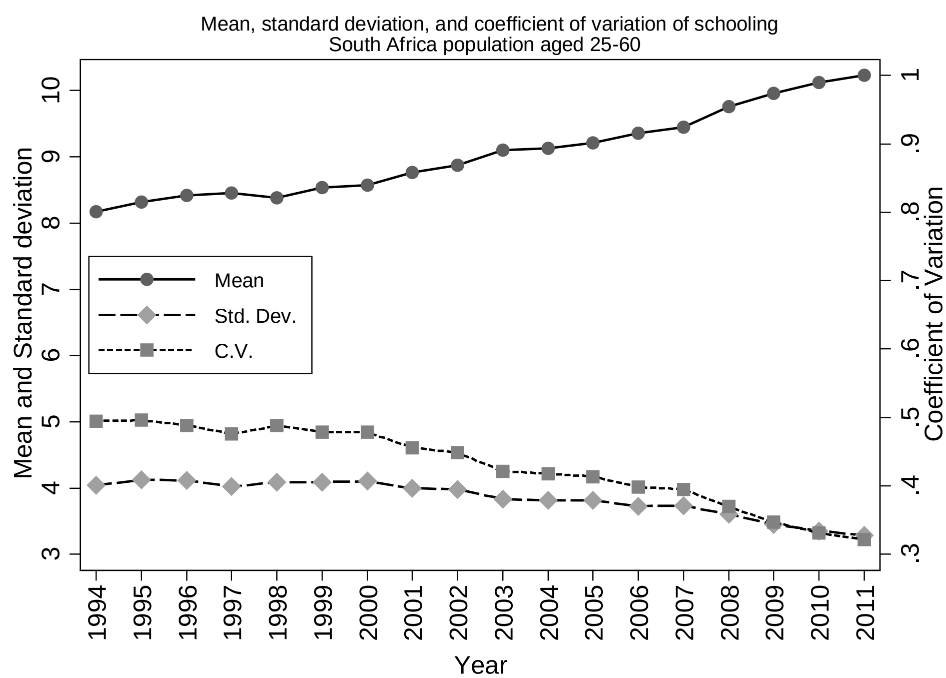
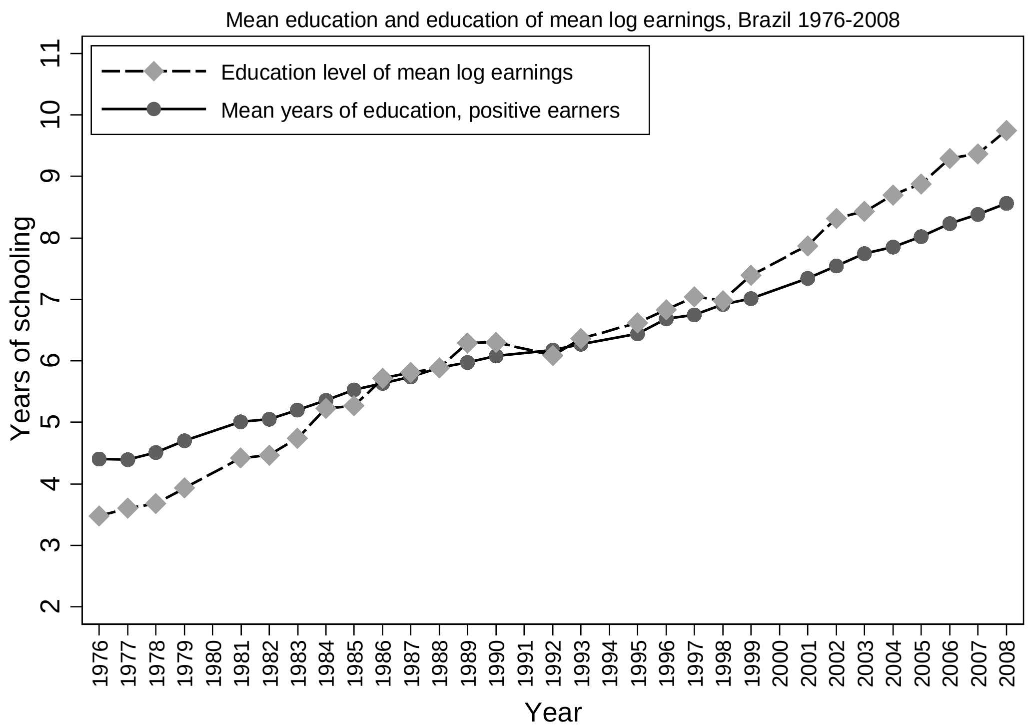


Figure 3. Mean years of schooling and schooling of mean log earnings,
Brazil and South Africa



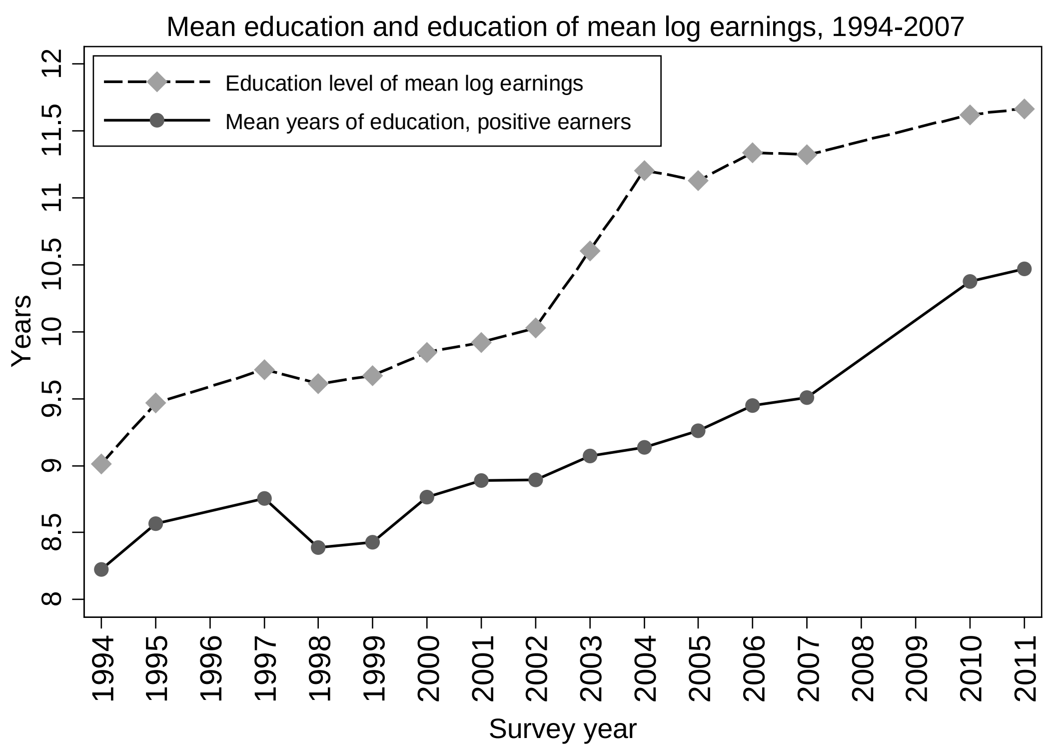


Figure 4. Average returns to schooling in schooling groups,
Brazil and South Africa