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COULD AN INCREASE IN EDUCATION RAISE INCOME INEQUALITY? EVIDENCE FOR LATIN AMERICA

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Could an Increase in Education Raise Income Inequality?

Evidence for Latin America [*]

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Abstract

This paper explores the direct effect of increasing education on the levels of earnings inequality by carrying out microsimulations for the Latin American countries. We find that the direct effect of the increase in education experienced by the region in the last two decades was unequalizing, and that this result is expected to hold for future improvements in education, a fact that is closely linked to the convexity of the returns to education.

Resumen

Este trabajo explora el efecto directo del aumento de la educación sobre la desigualdad salarial a través de microsimulaciones para todos los países de América Latina. El trabajo encuentra que el impacto directo del incremento educativo experimentado en la región en las últimas dos décadas fue desigualador, y que este resultado es esperable que se repita para futuras mejoras educativas. Estos resultados están estrechamente vinculados a la convexidad en los retornos a la educación.

Keywords: education, inequality, earnings, Latin America

JEL codes: I24, I25, D31.

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[*] This paper is part of a large project on inequality in Latin America and the Caribbean carried out at CEDLAS, the Center for Distributional, Labor and Social Studies at Universidad Nacional de La Plata.

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1. Introduction

Increasing education is one of the main ingredients in a typical recipe for development with equity. An upgrading in the human capital of a population is expected to contribute to higher productivity and hence a generalized increase in well-being, and also make a dent on income inequality. However, the link between education and income inequality may not be that straightforward. Given that there may be convexities in the returns to education, even an equalizing increase in schooling may generate an unequalizing change in the distribution of labor incomes. Bourguignon *et al*. (2004) have labeled this phenomenon "the paradox of progress", a situation where an educational expansion is associated to higher inequality. In this paper we explore whether this is just a theoretical possibility with little relevance in practice, or it is in fact a widespread phenomenon across real-world economies.

To that aim we carry out microeconometric decompositions that isolate the direct effect of changes in the distribution of education on earnings inequality. In particular we estimate the counterfactual distribution of individual earnings that would be generated in a given period t if the distribution of education took the observed values in t^* and the rest remained at their values in t. The difference between the real earnings distribution and the counterfactual one characterizes the direct impact of the change in the distribution of education on the earnings distribution. The methodology is applied to household survey microdata for the Latin American countries in the period 1990-2009, exploiting a dataset that contains homogeneous definitions for the education and labor variables involved in the analysis.

We find that the direct effect of the increase in education experienced by all countries in the region in the last two decades was unequalizing, a fact that is closely linked to the convexity of the returns to education. The paper includes simulations of alternative future changes in the distribution of education and concludes that even education reforms that lead to an equalizing increase in schooling may be associated to higher earnings inequality.

The rest of the paper is organized as follows. In section 2 we review the links between education and earnings and explain the possibility of a "progress paradox". In section 3 we explain the methodology of microeconometric decompositions and comment on the data used. Section 4 is aimed at presenting the results of applying the microsimulations to characterize changes in earnings inequality in Latin American countries during the last two decades, while section 5 presents projections of earnings inequality under alternative education upgrading scenarios. Section 6 closes with a discussion.

2. The theoretical link

Arguably, the most extended general policy advice for a developing country is to increase the educational level of its population. Without much discussion a reduction in inequality is often included in the list of the several positive consequences of an educational upgrade. However, if the returns to education are convex, an increase in schooling may lead to higher earnings inequality even when the upgrade is moderately biased toward the less educated groups. Bourguignon *et al*. (2004) have called this phenomenon “the paradox of progress”, a situation where the increase in education is accompanied by a surge in earnings inequality. In this section we illustrate this idea with a simple model.[1 2]

Consider first that the logarithm of individual earnings Y_i is related to the individual level of education X_i in a linear way. Ignoring other determinants for simplicity, this relationship at period t can be expressed as:

$$\ln Y_{it} = \alpha_t + \beta_t X_{it} + \varepsilon_{it} \tag{1}$$

where unobservable determinants can be summarized in the term ε_i.[3] Under the assumption of independence between X_i and ε_i parameter β is usually interpreted as a measure of the returns to education.

Assume that the whole set of earners can be divided into two groups H and L, with homogeneous education levels X_h and X_l respectively, and $X_h>X_l$, $E(\ln Y_h)>E(\ln Y_l)$. A simple measure of earnings-inequality in this two-group society is the expected proportional gap of earnings $E(\ln Y_h – \ln Y_l)$, that we label I. Taking conditional expectation on (1) and rearranging,

$$I \equiv E(\ln Y_{ht} - \ln Y_{lt}) = \beta_t (X_{ht} - X_{lt}) \tag{2}$$

From (2) the change in earnings inequality between periods 1 and 2 can be expressed as

$$\Delta I \equiv E(\ln Y_{h2} - \ln Y_{l2}) - E(\ln Y_{h1} - \ln Y_{l1}) = (\beta_2 - \beta_1)(X_{h1} - X_{l1}) + \beta_2 (dX_h - dX_l) \tag{3}$$

where dX_i is the change in the level of education for earners in group $i=h,l$. Equation (3) implies that the change in inequality depends on the changes in the returns to education over time ($\beta_2 – \beta_1$), the initial difference in education levels ($X_{h1} – X_{l1}$) and the relative change in education ($dX_h – dX_l$). If returns to education do not vary over time and the growth in educational levels is similar across groups, earnings inequality remains unchanged.

These results are modified when we allow the model to include convex returns to education. Assume that the logarithm of earnings and education are related through a quadratic function:

$$\ln Y_{it} = \alpha_t + \beta_t X_{it} + \gamma_t X_{it}^2 + \varepsilon_{it} \tag{4}$$

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[1] The link between education and inequality has been extensively addressed by economic literature. See, for instance, Soto (2002), Pritchett (2001), Krueger and Lindhal (2001), and Benhabib and Spiegel (1994).

[2] In this paper we concentrate on the short-run direct effect of education on earnings inequality.

[3] We also include the intercept parameter α, and then ε_i can be assumed to have zero-mean.

In such case, the expected change in the proportional gap of earnings between *H* and *L* takes the form:

(5)
$$\Delta I=(\beta_2-\beta_1)(X_{h1}-X_{l1})+\beta_2(dX_h-dX_l)+(\gamma_2-\gamma_1)(X_{h1}{}^2-X_{l1}{}^2)+ \\ +\gamma_2(dX_h{}^2-dX_l{}^2)+2\gamma_2(X_{h1}dX_h-X_{l1}dX_l)$$

Notice that when the returns to education remain unchanged and changes in education across groups are similar, equation (5) becomes $\Delta I=2\gamma_2(X_{h1}-X_{l1})dX$, which is positive under convex returns: inequality rises in response to an equal increase in education across the population. From (5), if returns to education do not change and returns are convex, even an unbalanced increase in education in favor of the unskilled group *L* may lead to a surge in earnings inequality. To see this, assume $dX_l=\lambda dX_h$ with $\lambda>1$. Earnings inequality *I* increases in this case if

(6)
$$X_{h1}-\lambda X_{l1}>\frac{1}{2}(\lambda-1)\left(\frac{\beta_2}{\gamma_2}+(\lambda-1)dX_h\right)$$

which is more likely to occur with highly convex returns to education.

3. Empirical strategy: microsimulations

This section presents an empirical strategy to provide evidence on the direct impact of changes in education on earnings inequality. The methodology follows closely Gasparini, Marchionni and Sosa Escudero (2005), which in turn is based on Bourguignon, Ferreira and Lustig (2005). It requires the estimation of earnings equations at the individual level, and the use of the resulting coefficients to construct counterfactual distributions. Earnings are modeled as parametric functions of observable characteristics, and the residuals of the regressions are interpreted as the effect of unobservable factors. In this section we describe the methodology that we follow to estimate the counterfactual distribution of individual earnings that would be generated in a given period *t* (or country *p*) if the distribution of education took the observed values in t^* (or p^*) and the rest remained at their values in *t* (or *p*). The difference between the real distribution and the counterfactual one characterizes the distributional impact of the change in the distribution of education.[4]

3.1. Empirical model

Following Gasparini *et al*. (2005), we can represent the individual-earnings generating process at time *t* as a function *F*:

(7)
$$\ln Y_{it} = F\left(X_{it},\, Z_{it},\, \varepsilon_{it},\, \beta_{xt},\, \beta_{zt}\right) \qquad i=1,\ldots,\, N$$

[4] Recall that we concentrate on the short-run direct effect of education on earnings inequality.

where:

Y_{it} = Individual earnings at time t

X_{it} = Vector of individual observable characteristics related to education at time t

Z_{it} = Vector of observable non-educational characteristics at time t

ε_{it} = Vector of individual non-observable characteristics at time t

β_{xt}, β_{zt} = Vectors of parameters that affect X_{it} and Z_{it} respectively

N = Total working population

The distribution of individual earnings can be characterized as follows:

(8) $$D_t = \{Y_{1t},\ \ldots, Y_{Nt}\}$$

Our aim is to evaluate how a change in the educational structure of the population affects earnings inequality. Therefore, our microsimulation strategy consists in estimating the counterfactual income that would arise if the educational structure were different from the actual structure. Particularly, we perform three types of simulations:

(i) Simulate the counterfactual earnings on year t assuming an educational structure similar to that observed in year t^*.

(ii) Simulate the counterfactual earnings of a country p assuming an educational structure similar to that observed in country p^*.

(iii) Simulate the counterfactual earnings that would arise under different education upgrading scenarios (*e.g.* an increase of one year of education for each worker in the sample).

The counterfactual logarithm of income for individual i in year t if X^* instead of X were observed can be defined as:[5]

(9) $$\ln Y_{it}\left(X_{it}^*\right) = F(X_{it}^*,\ Z_{it},\ \varepsilon_{it},\ \beta_{xt}, \beta_{zt}) \qquad i = 1,\ldots,N$$

The counterfactual earnings distribution is

(10) $$D_t\left(X^*\right) = \{Y_{1t}(X_{1t}^*),\ \ldots, Y_{Nt}(X_{Nt}^*)\}$$

Therefore, if we measure inequality by means of an index $I[D]$, the impact of the change in educational structure on earnings inequality can be estimated as:

(11) $$I\left[D_t\left(X^*\right)\right] - I\left[D_t\right]$$

3.2. Estimation strategy

[5] Note the importance of the exogeneity assumption regarding X, since our exercise implicitly assume that it can be replaced by X^* keeping ε_{it} unchanged.

In order to calculate (11), we need to obtain estimations of the vectors of parameters β_{xt}, β_{zt} and of the vector of unobservable characteristics ε_{it}. Moreover, given that no panel data is available for our purpose, we need some device in order to replicate the educational structure of one year (or country) into the population of another year (or country).

Estimation of β_{xt}, β_{zt} and ε_{it}

The estimations of β_{xt}, β_{zt} and ε_{it} are obtained from standard Mincer equations (Mincer, 1974), in which we model the logarithm of individual monthly earnings as a linear function of observable individual characteristics:

$$(12) \qquad \ln\left(Y_{it}\right) = X_{it}\beta_{xt} + Z_{it}\beta_{zt} + \varepsilon_{it} \qquad i = 1,\ldots,N$$

Education-related characteristics X_{it} are alternatively measured by a set of dummies of the highest educational level completed and by the number of years of formal education.

Simulation of X^*

In order to replicate the educational structure of year t^* (or country p^*) into the population of year t (or country p), we use two alternative methods. The first one was adapted from Gasparini *et al*. (2005) who propose to divide adult population of year t (or country p) in homogeneous age-gender cells and then replicate the levels of education of the corresponding cell from year t^* (or country p^*). The procedure requires the selection of individuals who are “moved” from one level of education to another until the desired structure is replicated. This selection is randomly performed, imposing the restriction that individuals move sequentially across levels.

The second procedure follows closely Legovini, Bouillon and Lustig (2004). Adult population of year t (or country p) is also divided into homogeneous age-gender cells j=1,2,…,J and for each individual i within cell j, we perform the following transformation over the variable years of education:

$$(13) \qquad X^*_{itj} = (X_{itj} - \mu_{tj})(\sigma^*_{tj} / \sigma_{tj}) + \mu^*_{tj} \qquad j = 1,2,...,J \;\; ; \;\; i = 1,2,...,N$$

where μ_{tj} , σ_{tj} are the sample mean and variance within cell j in year t (or country p) and μ^*_{tj} , σ^*_{tj} are the sample mean and variance estimated for the corresponding cell j in year t^* (or country p^*). For each cell in year t (or country p), this adjustment results in a distribution of the years of education with mean and variance similar to the corresponding cell in year t^* (or country p^*).

Counterfactual individual earnings

Once that the educational-structure from a different year (or country) is replicated into the adult working population, we estimate (9) using the parameters and unobservables estimated from (12) and assuming that observable non-educational characteristics remain constant for each individual.

3.3. Limitations of the approach

It is important to be aware of the limitations of the approach to make a careful interpretation of the results. First of all, the outlined approach provides estimations of the partial-equilibrium first-round impact of a change in the distribution of education on earnings inequality. Of course, if educational levels are modified, other variables that are fixed in the analysis may change, and then the final effect of a shock in education may be different from the direct impact. There are two main justifications for going ahead with the decompositions while admitting this important caveat: (i) estimating a full general equilibrium model that properly takes into account the movement of all the relevant variables is beyond the technical possibilities in many cases, and (ii) it is illustrative to know the direction and magnitude of the direct impact of a change, which in many applications turns out to be the most important.

There are other well-known limitations derived from the econometric specification of the model. One of them is that it is difficult to identify returns to education from returns to unobservable skills given that they are potentially correlated. Data limitations do not allow us to instrument educational variables (Angrist and Krueger, 1991) in order to obtain consistent estimations of the return to education. The other limitation, as we discuss later, is that parametric assumptions about the income generating process are not innocuous.

3.4. Dataset and methodological decisions

The main source of data for this paper is the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), jointly developed by CEDLAS at the Universidad Nacional de La Plata (Argentina) and the World Bank's LAC poverty group (LCSPP). This database contains information on more than 200 official household surveys in 25 LAC countries. All variables in SEDLAC are constructed using consistent criteria across countries and years, and identical programming routines (see sedlac.econo.unlp.edu.ar). In this paper we use microdata for 18 Latin American countries, covering the period 1990-2009.[6]

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[6] For comparison purposes in each country we restrict the sample to the areas covered by the national household survey in the whole period of analysis. Therefore, in Argentina we restrict the sample to the 15 main cities covered in the 1992 survey, in Brazil we exclude Rural-North areas included since 2004, and we only use urban areas from Uruguay (rural areas were added in 2006).

All calculations are performed using the subsample of workers aged 14 to 65 years and, following a standard procedure, we exclude from inequality measurement and Mincer estimations those individuals who do not receive any payment for their work. We define as dependent variable on Mincer equations the logarithm of monthly labor income. Given that the structural relationship between individual characteristics and earnings could be different for heads and other members of the household, we follow Gasparini *et al*. (2005) and estimate separately models for the head, the spouse of the head and other members.

As we discussed in previous sections, a key factor in the relationship between education and inequality is the convexity of the returns to education. Parametric assumptions about a particular functional form of these returns may modify the results. In our estimations we include education using two alternative definitions: (i) years of formal education and (ii) dummies for the highest educational level completed by each individual. The first definition, in which years of schooling is used as educational variable, allows us to obtain a parametric measure of the convexity of the returns by means of the coefficient of the squared variable. On the other hand, the dummies for educational levels allow us a more flexible estimation of the structure of the returns to education. As described above, we use a different simulation method for each type of educational variable. Notice that results from both types of simulations can substantially differ because there is not a direct correspondence between a change in years of education and a change in the share of workers with different levels of schooling. For instance, an increase in years of education could have little impact on the education structure if it is insufficient to move enough people to the subsequent level.

4. The results: characterizing past changes and country differences

In this section we present the results of applying the microsimulations to characterize changes in earnings inequality during the last two decades in 13 Latin American countries.[7] In particular, we seek to evaluate how changes in educational structures affected earnings inequality in that period. To this aim, we begin the section with a description of the changes in the educational structures in the period 1990-2009.

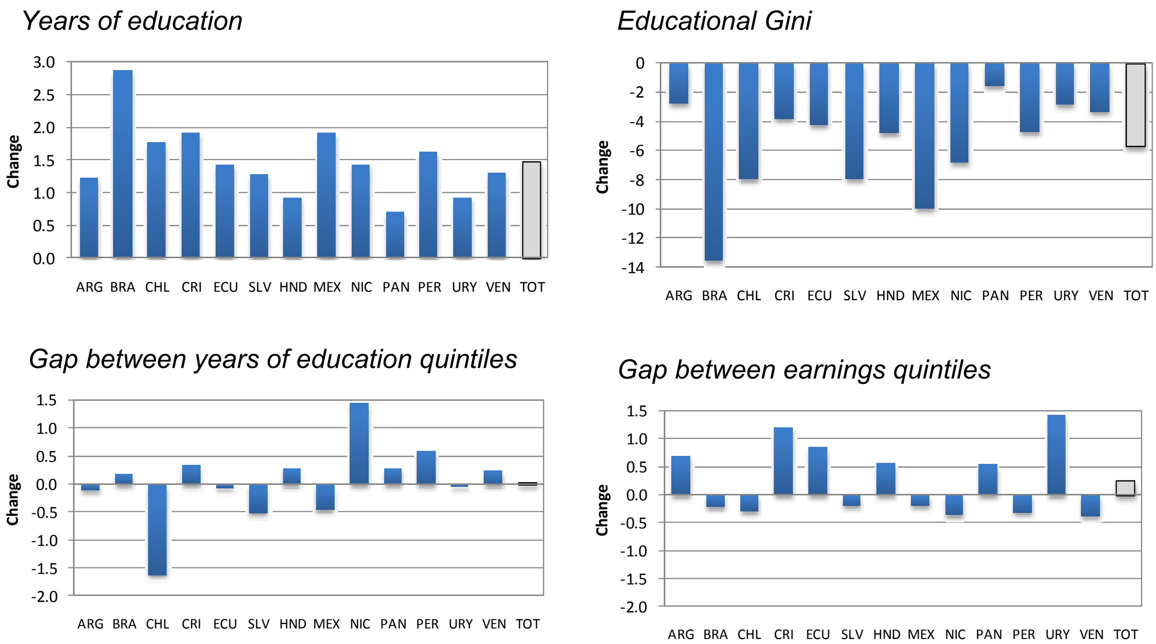
4.1. Changes in educational structures (1990-2009)

All countries in the region have experienced a substantial increase in education during the past two decades, that continues a process of educational upgrading initiated decades ago. On average, for the whole group of countries, the number of years of

[7] We do not include in the analysis all the LAC countries because data for the whole period under study is not available for some of them.

formal education for the working-age population grew by 1.5 years between 1990 and 2009 (see Figure 4.1 and Table A.1 in the Appendix).

Figure 4.1
Changes in years of education and in educational inequality during the period 1990-2009
Working-age population



Source: own calculations based on microdata from household surveys.
Note: TOT: Average for the whole group of countries.

We report three measures of educational inequality (Figure 4.1 and Table A.1). On the one hand, the educational Gini measures inequality in the distribution of years of schooling in relative terms and independently of income. Absolute inequality in education is captured by the difference in the average years of education between the top and bottom quintiles of that distribution (Gap 1). Finally, the difference in mean years of education between the richest and poorest earnings quintiles (Gap 2) is a measure that captures how unequal is the distribution of years of education relative to earnings.[8]

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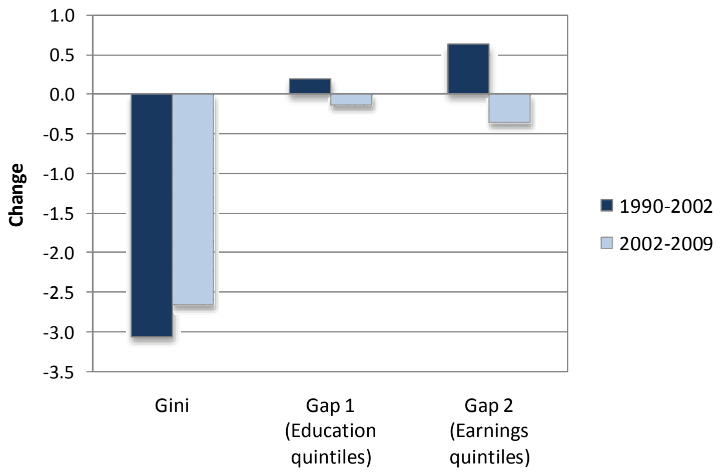
[8] Whether any change in educational structure should be evaluated using a relative or an absolute definition of inequality is a matter of subjective assessment. Nevertheless, for non-monetary variables, like education, it is sometimes more natural to evaluate changes in absolute terms rather than relative (Kolm, 1977). In the case of years of schooling distribution, an absolute inequality measure remains constant under identical additions of years of education to all individuals, whereas a relative indicator remains unchanged under proportional increments in this variable. For instance, if we multiply every individual's years of education by a constant, the Gini coefficient, which is a relative index, remains constant, whereas an absolute indicator, like the gap between the highest and the lowest quintile of education, increases.

During the last two decades education inequality measured by a relative index (Gini of years of education) fell in all countries, whereas results are mixed when using absolute indicators. The difference in years of education between extreme education quintiles dropped in three countries, increased in two and remained relatively unchanged in the rest. Measured by the gap between earnings quintiles, education became more unequal in six countries, whereas in the rest inequality slightly went down. The average educational Gini coefficient for the whole group of countries fell by 5.7 points, whereas the gap between years of education quintiles remained unchanged and the educational gap between earnings quintiles rose by 0.3 years.

Figure 4.2
Average changes for the group of countries in educational inequality



Source: own calculations based on microdata from household surveys.

Table A.2 in the Appendix splits changes in education during the whole period into two sub-periods: (1990-2002) and (2002-2009). Figure 4.2 summarizes the average changes in educational inequality for all countries. While the mean educational Gini substantially dropped in both periods; in contrast, the average educational gaps increased between 1990 and 2002, but decreased between 2002 and 2009. These results suggest that the education growth path was biased toward more educated (or richer) groups between 1990 and 2002 but slightly biased toward less educated (or poorer) groups between 2002 and 2009. This break in educational gaps can entail dissimilar effects on earnings inequality during each sub-period, as we will discuss later in this section.

4.2. Results from microsimulations

For each country/period Table 4.1 reports the actual change in the Gini coefficient of the earnings distribution, along with the counterfactual changes simulated by altering the educational structure. For Simulation 1 we use levels of education as the relevant educational variable, whereas in Simulation 2 we use years of formal education. Given that the results are path dependent, we alternatively simulate (i) the change in the Gini coefficient if the education structure of the first year of the period is simulated on the last year population and (ii) the change in the Gini coefficient if the education structure of the last year is simulated on the first year population. We report the average of the results obtained from each procedure.

Table 4.1
Effect of change in distribution of education on earnings inequality (Gini index)
Results from microeconometric decomposition

		Observed Gini			Education effect (Δ Gini)	
Country	Period	t_1	t_2	Change	Simulation 1	Simulation 2
Argentina	1992-2009	39.4	40.1	0.7	0.2 ***	1.2 ***
Brazil	1992-2009	50.4	51.1	0.7	1.0 ***	1.6 ***
Chile	1990-2009	52.5	50.2	-2.3	0.6 ***	0.7 ***
Costa Rica	1990-2009	40.0	45.4	5.4	0.9 ***	3.2 ***
Ecuador	1994-2009	53.3	45.5	-7.8	0.4 ***	2.1 ***
El Salvador	1995-2008	45.6	44.6	-1.0	2.5 ***	1.5 ***
Honduras	1995-2009	52.4	52.0	-0.4	1.7 ***	1.0 ***
Mexico	1989-2008	51.1	51.1	0.0	0.4 ***	1.0 ***
Nicaragua	1993-2005	53.6	49.4	-4.2	0.9 ***	1.3 ***
Panama	1991-2009	47.0	47.4	0.4	0.2 ***	2.0 ***
Peru	1997-2009	50.4	50.5	0.1	0.0	1.7 ***
Uruguay	1992-2009	44.9	47.7	2.8	-0.9 ***	0.5 ***
Venezuela	1992-2006	36.7	37.8	1.1	0.6 ***	0.7 ***
Average				*-0.3*	*0.6*	*1.4*

Source: own calculations based on microdata from household surveys.
Note: Simulation 1: Following Gasparini, Marchionni and Sosa Escudero (2004) procedure for changing educational structure. Simulation 2: Following Legovini, Bouillon and Lustig (2004) procedure for changing educational structure. Workers between 14 and 65.
(*) Significance levels obtained using 200 bootstrap repetitions.

The interpretation of Table 4.1 is straightforward. For example, in the case of Brazil the Gini index of the labor earnings increased 0.7 between 1992 and 2009. Simulation 1 reveals that the effect of changes in education on earnings distribution was an increase of approximately 1 point in the Gini coefficient.[9] This value can be interpreted as the isolated effect of the change in education structure on earnings inequality, that is, if only the educational structure had changed during that period, the Gini coefficient of earnings distribution would have increased by 1 point.

From the whole sample of 13 countries considered in Simulation 1 we infer that changes in educational structures (measured by levels of education) increased earnings inequality in 11 countries, whereas these changes had an equalizing effect

[9] There are three cases (Argentina, Chile and Peru) where path dependency in Simulation 1 results in opposite sign changes when using the first rather than the last year as benchmark. Conversely, Simulation 2 presents no sign ambiguity regarding the base year used for replicating educational structure.

only in Uruguay.[10] As mentioned before, Simulation 2 uses years of education instead of levels of schooling in order to measure changes in education structures. In this case, the estimated effects are always unequalizing. In addition, increases in inequality are more pronounced than those estimated in Simulation 1 for most countries.

Table 4.2 splits the results from Table 4.1 in sub periods: (1990-2002) and (2002-2009). The outcomes from Simulation 1 indicate that during the first sub-period changes in education structures produced on average a 0.6 increase in the simulated Gini of earnings, whereas between 2002 and 2009 the average simulated increase was 0.2. Simulation 2 implies similar pattern: the average simulated increase in the Gini of earnings was about 1.3 between 1990 and 2002 but only 0.4 between 2002 and 2009.

Both simulations suggest that the changes in underlying educational structures were more unequalizing during the first sub-period. This result is consistent with the observed tendency break of educational gaps documented in Table A.2, where on average both gaps increased between 1990 and 2002, but dropped during 2002-2009. The combination of convex returns (as we will see below) with educational improvements biased toward the most educated (or richer) groups, resulted in a higher unequalizing effect on earnings distribution during the first sub-period. In contrast, during the second period educational changes seemed to be slightly biased toward less educated (or poorer) groups, a fact that resulted in a lower unequalizing effect on earnings. In fact, there are some countries (Argentina, Chile, Honduras, Peru and Uruguay) where educational improvements had an equalizing effect on earnings during the second sub-period.

Table 4.2
Effect of change in distribution of education on earnings inequality (Gini index)
Results from microeconometric decomposition

[10] Similarly, Bourguignon *et al*. (2004), found that in five of the seven studied countries (Argentina, Colombia, Mexico, Indonesia and Malaysia) the effect of educational expansions was to increase inequality. Other authors also reported similar results for other countries (Langoni, 1973; Almeida dos Reis and Paes de Barros, 1991; Knight and Sabot, 1983; Reyes, 1988; Lam, 1999).

Around 1990-2002

Country	Period	Δ Observed Gini	Education effect (Δ Gini) Simulation 1	Simulation 2
Argentina	1992-2004	5.5	0.4 ***	1.3 ***
Brazil	1992-2002	5.1	0.5 ***	1.6 ***
Chile	1990-2003	0.4	0.4 ***	0.6 ***
Costa Rica	1990-2002	5.9	1.0 ***	2.1 ***
Ecuador	1994-2003	-2.6	-0.6 ***	2.2 ***
El Salvador	1995-2002	1.9	2.3 ***	0.9 ***
Honduras	1995-2002	1.0	0.5 ***	1.4 ***
Mexico	1989-2002	-0.7	0.2 **	1.1 ***
Nicaragua	1993-2001	3.7	1.0 ***	1.5 ***
Panama	1991-2002	5.7	0.2 ***	1.8 ***
Peru	1997-2003	4.8	0.6 ***	1.8 ***
Uruguay	1992-2002	3.2	0.9 ***	0.5 ***
Venezuela	1992-2002	6.6	0.6 ***	0.7 ***
Average		*3.1*	*0.6*	*1.3*

Around 2002-2009

Country	Period	Δ Observed Gini	Education effect (Δ Gini) Simulation 1	Simulation 2
Argentina	2004-2009	-4.8	-0.3 ***	0.1 ***
Brazil	2002-2009	-4.4	0.8 ***	1.7 ***
Chile	2003-2009	-2.8	-0.3 ***	-0.1 **
Costa Rica	2002-2009	-0.6	0.1	0.7 ***
Ecuador	2003-2009	-5.2	1.5 ***	0.1 *
El Salvador	2002-2008	-3.0	0.0	1.0 ***
Honduras	2002-2009	-1.4	1.0 ***	-0.6 ***
Mexico	2002-2008	0.7	0.6 ***	0.4 ***
Nicaragua	2001-2005	-7.9	0.5 ***	1.3 ***
Panama	2002-2009	-5.3	0.0	0.4 ***
Peru	2003-2009	-4.7	-0.1 *	0.3 ***
Uruguay	2002-2009	-0.4	-1.6 ***	-0.1 ***
Venezuela	2002-2006	-5.5	0.1 ***	0.3 ***
Average		*-3.5*	*0.2*	*0.4*

Source: own calculations based on microdata from household surveys.
Note: Simulation 1: Following Gasparini, Marchionni and Sosa Escudero (2004) procedure for changing educational structure. Simulation 2: Following Legovini, Bouillon and Lustig (2004) procedure for changing educational structure. Workers between 14 and 65.
(*) Significance levels obtained using 200 bootstrap repetitions.

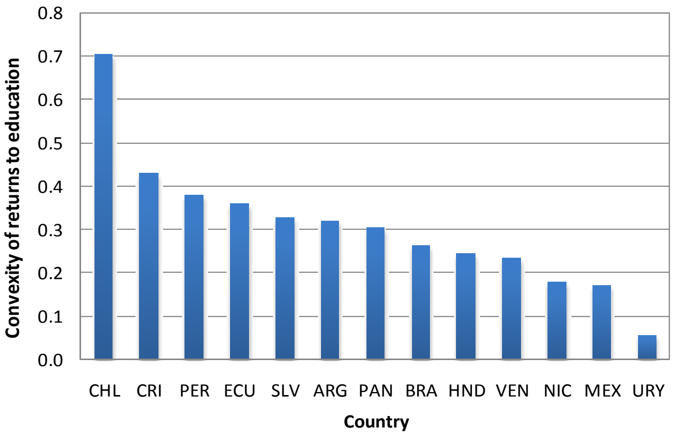
Convexity of the returns to education

As we discussed in section 2, the way in which education affects earnings inequality critically depends on the convexity of the returns to education. Figure 4.3 reports the estimated average coefficient of the variable *years of education squared*, which can be interpreted as a measure of convexity of the returns to education.[11] From Figure 4.3 it

[11] Given that we estimate separately Mincer equations for head, spouse, and other members of the household, we average the coefficients of these regressions for all type of members and all periods of analysis. Coefficients are comparable since dependent variables in all Mincer

can be seen that convexity in returns to education is a common characteristic for all countries in the sample.[12] [13]

Figure 4.3
Average convexity of returns to education
Results obtained from estimated Mincer equations



Source: own calculations based on microdata from household surveys.

This result imposes a harder requirement to educational improvements in order to reduce inequality, according to the theoretical model described in section 2.[14] Recall that the model shows that if returns to education do not vary over time[15], linear returns assure that an increase in education slightly biased toward less educated (or poorer) groups is enough to reduce earnings inequality. Nevertheless, under convex returns, even an unbalanced increase in education in favor of the less educated (or poorer) groups may lead to a surge in earnings inequality. Moreover, the higher convexity, the greater the bias toward the more disadvantaged groups must be in order to make the distribution of individual earnings more equal (equation (6)). As we have shown, even

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equations are expressed in 2005 PPP dollars and independent variables are homogeneously constructed using SEDLAC definitions.

[12] This conclusion remains valid for all countries if we consider separated coefficients instead of averaged coefficients, with the exception of Nicaragua that shows a negative (though very low) coefficient for spouse's regression.

[13] These results are consistent with Bourguignon *et al*. (2004), who found that in the seven studied economies, earnings and also their logarithms were, in general, convex functions of the years of schooling.

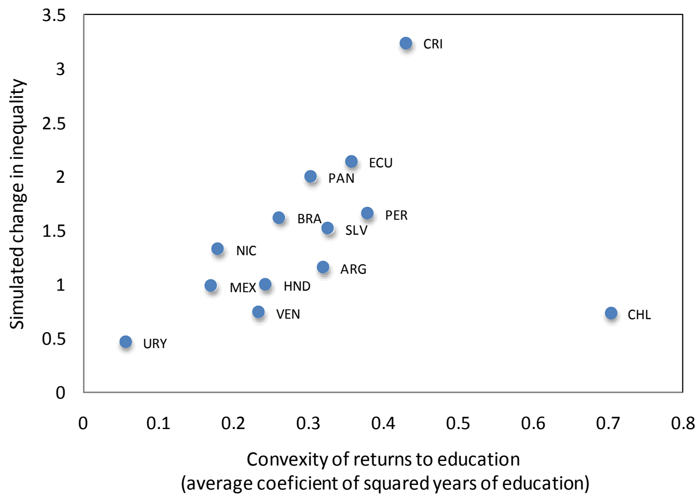
[14] Convexity condition in our model is defined as "*logarithmic convexity*" of the returns to education. As noted by Bourguignon *et al*. (2004), if we increase proportionally the years of education of every worker, a stronger condition is required to keep inequality unchanged. In terms of our model, this condition can be stated as "*strong convexity*" of returns to education with respect to earnings (instead of logarithms of earnings). Our estimations suggest that in all countries, returns are strongly convex respect to earnings, meaning that the education inequality should drop in a significant amount in order to reduce earnings inequality.

[15] Just like we assume in our empirical strategy (since our main purpose is to isolate the distributional effect of the changes in education structure, in the simulations, only the educational structure is changed whereas the parameters are left constant).

though education seems to be more equally distributed in several countries, changes were not progressive enough to reduce earnings inequality.

Figure 4.4 shows the estimated relationship between the convexity of returns to education and the counterfactual changes in inequality (measured as the changes in Gini coefficients as reported in Table 4.1 for Simulation 2). There is a clear positive relationship with Chile as the only outlier (high convexity but a low increase in simulated inequality). This positive relationship means that the educational improvements during the last two decades brought about a higher unequalizing effect on earnings distribution in those countries with higher convexity in the returns to education.

Figure 4.4
Estimated relationship between convexity and simulated changes in inequality
Results from microeconometric decomposition



Source: own calculations based on microdata from household surveys.

Examining the determinants of the change in earnings inequality

In this section we take a preliminary view of some of the determinants of the change in earnings inequality based on the analysis of section 2. Table 4.3 shows the correlation between the simulated changes in earnings inequality and changes in some educational variables. The positive correlation with mean years of education indicates that those countries that experienced a greater increase in education during the period under analysis underwent a larger growth in simulated earnings inequality. Given that all countries show convex returns and that the increases in years of education were, on average, roughly balanced across groups, a positive correlation between inequality and education changes is an expected result, according to the model presented in section 2 (assuming that returns to education do not vary over time). The correlations are higher when considering measures of education inequality. In this case, positive values indicate that the higher increase (or the lower decrease) in educational inequality, the greater the simulated rise in earnings inequality.

Table 4.3
Correlation between simulated change in earnings inequality and change in educational structure

Correlation between simulated change in earnings inequality and change in…	
Years of education	0.165
Gini of years of education	0.264
Gap 1 (Education quintiles)	0.268
Gap 2 (Earnings quintiles)	0.201

Source: own calculations based on microdata from household surveys.
Note: Years of education: Mean of years of education. Gap 1: Educational gap between years of education quintiles. Gap 2: Educational gap between earnings quintiles. Workers between 14 and 65.

According to the model in section 2 the initial difference in education also affects earnings inequality. Table 4.4 shows the correlation between simulated changes in earnings inequality (estimated from Simulation 2) and the initial differences in education levels (measured by the educational gaps observed in the first year of the period). Correlations are positive, which implies that increasing education gave rise to a larger growth in simulated earnings inequality in those countries that had a greater educational gap in the first year. Again, considering returns to education unchanged, since all countries show convex returns and the changes in education were, on average, roughly balanced across groups, this is an expected result according to the model.

Table 4.4
Correlation between simulated change in earnings inequality and the initial difference in education levels

Correlation between simulated change in earnings inequality and…	
Gap 1 (Education quintiles) in t_1	0.072
Gap 2 (Earnings quintiles) in t_1	0.268

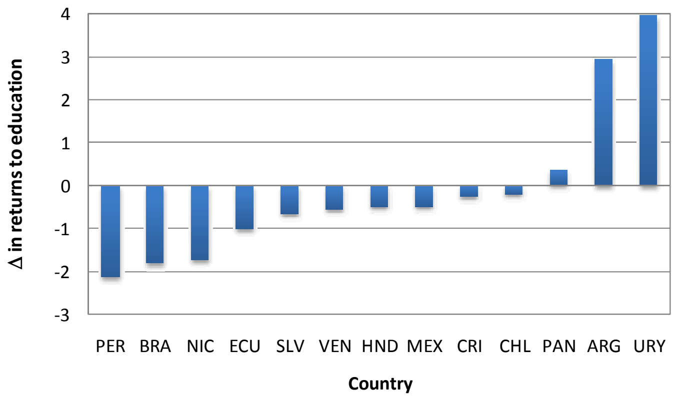
Source: own calculations based on microdata from household surveys.
Note: Gap 1: Educational gap between years of education quintiles. Gap 2: Educational gap between earnings quintiles. Workers between 14 and 65.

The theoretical model shows that changes in returns to education can also affect earnings inequality. Measuring this effect is however beyond the scope of this paper[16].

[16] The effect of the change in structural parameters on inequality is usually defined by literature as "Parameter effect" or "Price effect". Its estimation is straightforward from the methodology described in section 3. Notice that simulated changes in Gini reported in Table 4.1 do not include this effect.

In Figure 4.5 we show the estimated changes, measured by the change in the first order derivative of the Mincer equation respect to years of education (evaluated at the first period average years of education). In all countries except Panama, Argentina and Uruguay, returns to education have declined during the period. According to our model, a decrease in returns to education has an equalizing impact on the earnings distribution.

Figure 4.5
Changes in returns to education during the period of analysis
Change in average first derivative of the Mincer equation respect to years of education



Source: own calculations based on microdata from household surveys.

4.3. Characterizing differences across countries

An alternative exercise to be carried out is a series of simulations across countries to assess how differences in educational structures can explain the observed differences in labor income inequality across countries. Table A.3 and Table A.4 in the Appendix report for each country in rows, the counterfactual change in Gini of earnings simulated by replicating the educational structure of the country in the respective column. For instance, if in Argentina we simulate an educational structure similar to that observed in Bolivia, the Gini coefficient would be 2.7 points higher than the actually observed. Conversely, inequality would be lower if educational structure were similar to those observed in Costa Rica, Panama or Uruguay. Similarly to previous simulations, in Table A.3 we use completed levels of education as the relevant educational variables whereas in Table A.4 we use years of formal education and its square.

Two opposite patterns stand out from Tables A.3 and A.4. On the one hand, if educational structure from Bolivia, Dominican Republic, Ecuador, Mexico or Peru were imposed on other countries, earnings inequality would raise in most countries. On the other hand, if education structure from Costa Rica or Uruguay were simulated, earnings inequality would drop in most countries. For the rest of the countries, the results depend on the simulated structure and the definition of the education variable (years or levels).

5. The results: projecting the future

Along the previous section we discussed how past educational changes influenced the levels of earnings inequality. It is likewise interesting to analyze how future changes in educational patterns would affect inequality. In this section we use microeconometric decompositions to simulate the impact of alternative growth paths of the education variables on the inequality measures. Results rest on the crucial assumption that the returns to education are not modified as education expands.

5.1. Results from microsimulations

Table 5.1 reports the simulated changes in earnings inequality driven by two counterfactual changes in education structure:

i) An increase of one year of education for each worker in the sample (Simulation 3).

ii) A proportional change that increases the average years of education in one year (Simulation 4).

As Table 5.1 shows, if we assume that returns to education remain constant, the effect of one year more of education for every worker (Simulation 3) is undoubtedly unequalizing in all countries. Since the change in education is assumed to be balanced across less- and more-skilled groups, this example illustrates the standing role of the convexity of the returns to education. Unsurprisingly, a change in education biased toward more educated groups, like the proportional increase in years of education assumed in Simulation 4, raises earnings inequality in all countries even more than Simulation 3.[17]

Table 5.1
Effect of an extra year of education on earnings inequality
Results from microeconometric decomposition

[17] Note that, like in the previous section, not only convexity of the returns to education is determinant for these results, but also the initial distribution of years of education can explain the magnitude of the changes in earnings inequality.

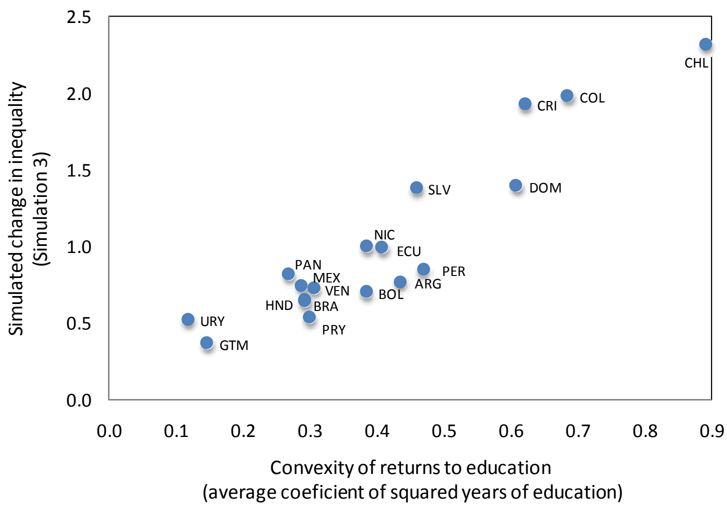
Country	Year	Observed Gini	Effect of one year more of formal education				Convexity of returns
			Simulation 3		Simulation 4		
			Gini	Δ Gini	Gini	Δ Gini	
Argentina	2009	40.1	40.9	0.8 ***	41.9	1.8 ***	0.44
Bolivia	2005	53.9	54.6	0.7 ***	56.1	2.2 ***	0.38
Brazil	2009	51.1	51.8	0.6 ***	53.4	2.3 ***	0.29
Chile	2009	50.2	52.5	2.3 ***	54.4	4.3 ***	0.89
Colombia	2007	53.4	55.4	2.0 ***	58.6	5.2 ***	0.69
Costa Rica	2009	45.4	47.3	1.9 ***	50.1	4.7 ***	0.62
Dominican Rep.	2009	46.6	48.0	1.4 ***	49.9	3.3 ***	0.61
Ecuador	2009	45.5	46.5	1.0 ***	48.1	2.6 ***	0.41
El Salvador	2008	44.6	45.9	1.4 ***	48.6	4.0 ***	0.46
Guatemala	2006	52.3	52.7	0.4 ***	55.3	3.0 ***	0.15
Honduras	2009	52.0	52.7	0.6 ***	55.1	3.1 ***	0.29
Mexico	2008	51.1	51.9	0.7 ***	53.6	2.4 ***	0.29
Nicaragua	2005	49.4	50.4	1.0 ***	52.8	3.4 ***	0.39
Panama	2009	47.4	48.3	0.8 ***	50.0	2.6 ***	0.27
Paraguay	2009	48.7	49.2	0.5 ***	50.4	1.7 ***	0.30
Peru	2009	50.5	51.4	0.8 ***	52.4	1.9 ***	0.47
Uruguay	2009	47.7	48.3	0.5 ***	49.7	2.0 ***	0.12
Venezuela	2006	37.8	38.5	0.7 ***	39.8	2.0 ***	0.31

Source: own calculations based on microdata from household surveys.
Note: Simulation 3: One year more of education for each individual in the sample. Simulation 4: Proportional change increasing in one year the mean years of education in the sample. Convexity of returns estimated as the average coefficient (x100) of squared years of education for "head", "spouse" and "other members" Mincer equations. Workers between 14 and 65.
(*) Significance levels obtained using 200 bootstrap repetitions.

Both simulations point out that the highest counterfactual increases in inequality are more likely in Chile, Colombia and Costa Rica, whereas the lowest changes would occur in Guatemala, Uruguay and Paraguay. These results, particularly for Simulation 3, show a high positive correlation with the estimated convexity of the returns to education as reported in the last column of Table 5.1 and in Figure 5.1.[18] Once more, this confirms the presumptions of section 2, that is, the higher convexity of the returns to education, the greater will be the unequalizing effect on earnings distribution of an increase of one year of education for each individual (keeping the returns unchanged).

Figure 5.1
Estimated relationship between convexity and simulated changes in earnings inequality
Results from microeconometric decomposition (Simulation 3)

[18] Like before, convexity of the returns to education is measured by means of the average coefficient of squared years of education in Mincer equations for head, spouse and other members of the household.



Source: own calculations based on microdata from household surveys.

5.2. Characterizing inequality-reducing educational growth paths

As we noted before, results from Simulations 3 and 4 are consistent with the theoretical model: a proportional increase in years of education or even a uniform increase for all workers would result in higher earnings inequality under convex returns. We can examine the conditions under which an increase in education would produce a fall in inequality. With this aim, we define the following transformation that will be used to simulate an average increase of one year of education (X) under different educational growth paths:

$$X_i^* = X_i + \alpha\left(1 - \frac{X_i}{X_{\max}}\right)^{\delta} \;;\; \alpha > 0 \tag{14}$$

We impose the following restriction:

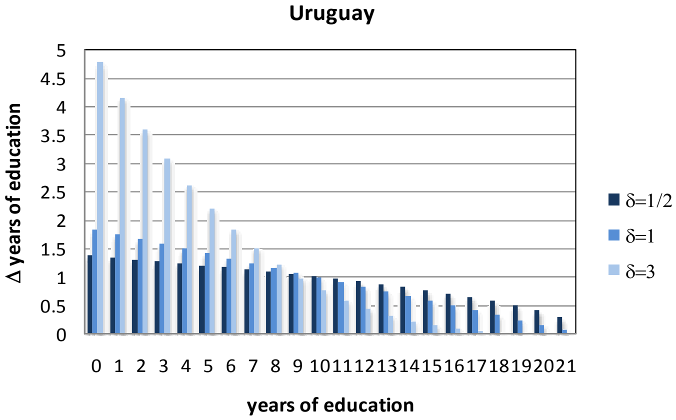
$$\frac{1}{N}\sum_i X_i + 1 = \frac{1}{N}\sum_i \left[X_i + \alpha\left(1 - \frac{X_i}{X_{\max}}\right)^{\delta} \right] \tag{15}$$

Equation (14) defines the transformation as a function of two exogenous parameters δ and α. X_{max} is the highest value of the variable years of education in the sample. The higher the value of parameter δ, the more intense the increase in education for the less educated relatively to those more educated.[19] Equation (15) restricts the transformation to simulate an average increase of one year of education. When δ=0, then α=1 and the change in educational structure matches Simulation 3.

[19] Particularly, values of δ>0 imply that in absolute terms the increase in years of education is biased toward less educated population. Negative values of δ result in a change biased toward more educated population.

Figure 5.2 shows the underlying changes in years of education for different values of δ using Uruguay's sample.[20] As the figure shows, a value of δ=3 implies an extremely biased change toward less educated, whereas δ=1 and δ=1/2 are still changes biased toward less educated population.

Figure 5.2
Changes in years of education using different values of δ



Source: own calculations based on microdata from household surveys.

Table 5.2 reports the simulated changes in earnings inequality when the average years of educations is increased by one year, assuming different values of δ. Additionally, in order to illustrate how significant is the change produced in the educational structure, for each value of δ, we report the change in education inequality by means of the educational Gini and the educational gap between earnings quintiles. We expect that earnings inequality is more likely to fall for higher values of δ.

The simulations suggest that in 12 of the 18 countries a value of δ>1/2 is required to yield an educational growth with decreasing inequality and in some cases like Dominican Republic or El Salvador a value of δ>1 is required for this to happen. The requirement of δ>1/2 is strong taking into account that δ=0 implies a uniform change (changes in the educational Gini and in the educational gap between earnings quintiles reported in Table 5.2 confirm this). Therefore, our estimations show that even when educational change is assumed to be biased toward those less-skilled, earnings inequality will raise if the increase in education is not progressive enough.

Table 5.2
Effect of an extra year of education on earnings inequality
Results from microeconometric decomposition

[20] The rest of the countries show figures very similar to this.

			Effect of one year more of formal education								
		Observed Gini earnings	δ=1/2			δ=1			δ=3		
			Earnings	Education		Earnings	Education		Earnings	Education	
Country	Year		Δ Gini	Δ Gini	Δ Gap	Δ Gini	Δ Gini	Δ Gap	Δ Gini	Δ Gini	Δ Gap
Argentina	2009	40.1	0.0	-2.6	-0.1	-0.4 ***	-3.5	-0.8	-1.1 ***	-6.0	-1.7
Bolivia	2005	53.9	-0.2 **	-5.2	-0.5	-0.4 ***	-6.4	-0.9	-0.7 ***	-9.2	-1.7
Brazil	2009	51.1	-0.1 ***	-5.6	-0.3	-0.6 ***	-6.8	-0.8	-1.4 ***	-10.0	-1.9
Chile	2009	50.2	0.7 ***	-2.4	0.2	-0.1	-3.2	-0.3	-1.0 ***	-5.8	-1.4
Colombia	2007	53.4	0.4 ***	-4.5	0.0	-0.2 ***	-5.6	-0.5	-0.9 ***	-8.5	-1.4
Costa Rica	2009	45.4	0.3 ***	-3.8	-0.2	-0.4 ***	-4.9	-0.6	-1.3 ***	-7.4	-1.4
Dominican Rep.	2009	46.6	0.6 ***	-4.4	0.3	0.2	-5.4	-0.1	-0.3 ***	-8.5	-1.1
Ecuador	2009	45.6	0.2 ***	-4.6	-0.1	-0.2 ***	-5.7	-0.6	-0.6 ***	-8.4	-1.4
El Salvador	2008	44.6	0.5 ***	-5.4	-0.1	0.1	-6.4	-0.4	-0.6 ***	-9.4	-1.3
Guatemala	2006	52.3	-0.2 ***	-8.9	-0.4	-0.6 ***	-10.1	-0.7	-1.1 ***	-13.4	-1.5
Honduras	2009	52.0	0.1 **	-5.6	-0.1	-0.3 ***	-6.6	-0.5	-0.7 ***	-9.6	-1.2
Mexico	2008	51.1	0.0	-3.9	-0.3	-0.4 ***	-4.9	-0.7	-1.0 ***	-7.6	-1.5
Nicaragua	2005	49.4	0.0	-7.5	0.0	-0.2 **	-8.9	-0.4	-0.4 ***	-12.3	-0.9
Panama	2009	47.4	-0.2 ***	-3.3	-0.3	-0.8 ***	-4.2	-0.9	-1.5 ***	-6.8	-1.9
Paraguay	2009	48.7	-0.2 ***	-4.6	-0.6	-0.4 ***	-5.7	-1.0	-0.7 ***	-8.4	-1.7
Peru	2009	50.5	0.0	-6.2	-0.2	-0.2 ***	-7.5	-0.6	-0.4 ***	-10.6	-1.4
Uruguay	2009	47.7	-0.2 ***	-2.8	-0.3	-0.6 ***	-3.6	-0.7	-1.4 ***	-5.8	-1.5
Venezuela	2006	37.8	0.0 *	-4.0	-0.3	-0.3 ***	-5.1	-0.7	-0.8 ***	-7.9	-1.5

Source: own calculations based on microdata from household surveys.
Note: Values of δ according with the transformation $X_i^* = X_i + \alpha\left(1 - X_i / X_{max}\right)^{\delta}$. Gap: Educational gap between earnings quintiles. Workers between 14 and 65.
(*) Significance levels obtained using 200 bootstrap repetitions.

6. Concluding remarks

We find that the direct effect of the increase in education experienced by Latin American countries in the last two decades was unequalizing, and that this result is expected to hold for future improvements in education. Both facts are closely linked to the convexity of the returns to education. With convex returns even a progressive change in education may lead to a more unequal distribution of earnings and hence to a more unequal income distribution. The paper shows that this is not just a theoretical possibility with little relevance in practice but it is in fact a widespread phenomenon across Latin American economies.

Of course, showing that an increase in education may be linked to an increase in inequality does not lead to the advice of reducing investment in education. Indeed, indirect and long run effects and general equilibrium spillovers could offset the unequalizing direct impact of education.

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Appendix

Table A.1
Years of education and educational inequality
Working-age population

Country		Years of education	Educational inequality: Gini years of education	Gap 1 (Education quintiles)	Gap 2 (Earnings quintiles)
Argentina	1992	10.2	21.4	10.5	3.7
	2009	11.4	18.6	10.4	4.4
Brazil	1992	5.5	43.5	12.1	6.2
	2009	8.4	30.0	12.3	6.0
Chile	1990	9.8	25.0	12.0	4.7
	2009	11.6	17.0	10.4	4.4
Costa Rica	1990	7.3	29.6	11.1	5.2
	2009	9.3	25.8	11.5	6.4
Ecuador	1994	7.6	33.9	13.1	5.0
	2009	9.0	29.7	13.0	5.8
El Salvador	1995	6.6	44.3	14.3	7.7
	2008	7.9	36.3	13.7	7.5
Honduras	1995	5.5	42.7	12.2	5.2
	2009	6.4	37.9	12.5	5.7
Mexico	1989	7.2	37.9	13.1	6.1
	2008	9.1	27.9	12.7	5.9
Nicaragua	1993	5.0	48.0	11.7	5.0
	2005	6.5	41.1	13.1	4.6
Panama	1991	9.8	25.8	12.3	6.5
	2009	10.5	24.3	12.5	7.1
Peru	1997	7.6	33.3	12.5	5.3
	2009	9.2	28.5	13.1	5.0
Uruguay	1992	9.1	24.4	10.8	3.6
	2009	10.0	21.5	10.7	5.0
Venezuela	1992	7.9	30.2	12.0	5.7
	2006	9.2	26.9	12.3	5.3

Source: own calculations based on microdata from household surveys.
Note: Years of education: Mean of years of education. Gap 1: Educational gap between years of education quintiles. Gap 2: Educational gap between earnings quintiles. Workers between 14 and 65.

Table A.2
Changes in education during the period
Working-age population

Around 1990-2002

Country	Period	Years of education	Educational inequality		
			Gini of years of education	Gap 1 (Education quintiles)	Gap 2 (Earnings quintiles)
Argentina	1992-2004	0.9	-1.6	0.0	0.9
Brazil	1992-2002	1.6	-7.7	0.0	0.5
Chile	1990-2003	1.4	-6.2	-1.2	0.3
Costa Rica	1990-2002	1.1	-1.8	0.4	1.0
Ecuador	1994-2003	1.0	-2.5	0.3	1.3
El Salvador	1995-2002	0.9	-6.3	-0.6	-0.7
Honduras	1995-2002	0.3	0.6	0.7	1.5
Mexico	1989-2002	1.2	-5.9	0.3	1.1
Nicaragua	1993-2001	0.7	-3.9	0.9	-0.8
Panama	1991-2002	-0.1	1.4	0.6	1.2
Peru	1997-2003	0.9	-1.9	0.7	0.7
Uruguay	1992-2002	0.9	-2.2	0.1	1.2
Venezuela	1992-2002	0.8	-2.0	0.2	0.0
Average changes		*0.9*	*-3.1*	*0.2*	*0.6*

Around 2002-2009

Country	Period	Years of education	Educational inequality		
			Gini of years of education	Gap 1 (Education quintiles)	Gap 2 (Earnings quintiles)
Argentina	2004-2009	0.3	-1.3	-0.2	-0.2
Brazil	2002-2009	1.3	-5.9	0.2	-0.7
Chile	2003-2009	0.4	-1.8	-0.4	-0.6
Costa Rica	2002-2009	0.9	-2.0	-0.1	0.2
Ecuador	2003-2009	0.4	-1.7	-0.3	-0.4
El Salvador	2002-2008	0.4	-1.7	0.1	0.5
Honduras	2002-2009	0.6	-5.4	-0.5	-1.0
Mexico	2002-2008	0.7	-4.0	-0.7	-1.3
Nicaragua	2001-2005	0.8	-2.9	0.6	0.4
Panama	2002-2009	0.8	-3.0	-0.3	-0.7
Peru	2003-2009	0.7	-2.9	-0.2	-1.0
Uruguay	2002-2009	0.1	-0.7	-0.1	0.2
Venezuela	2002-2006	0.5	-1.4	0.0	-0.4
Average changes		*0.6*	*-2.7*	*-0.1*	*-0.4*

Source: own calculations based on microdata from household surveys.
Note: Years of education: Mean of years of education. Gap 1: Educational gap between years of education quintiles. Gap 2: Educational gap between earnings quintiles. Workers between 14 and 65.

Table A.3
Change in Gini from microeconometric cross-country decompositions

	Education structure of country…																
Country	Arg	Bol	Bra	Chl	Col	Cri	Dom	Ecu	Slv	Gtm	Mex	Nic	Pan	Pry	Per	Ury	Ven
Arg	-	2.7	1.8	0.2	0.5	-0.8	2.1	0.7	2.0	0.8	1.2	0.9	-0.4	0.7	1.5	-0.7	0.3
Bol	-0.6	-	-0.3	-1.0	-1.4	-2.1	0.2	-1.2	-0.3	-1.3	-1.3	-1.2	-1.4	-1.4	0.2	-2.2	-1.1
Bra	-1.3	1.0	-	-1.3	-1.0	-3.1	0.1	-1.0	-0.4	-2.0	-0.4	-1.6	-1.9	-1.4	0.1	-2.1	-1.3
Chl	0.4	1.2	0.2	-	-0.1	-2.6	0.5	0.4	-0.9	-2.5	0.4	-1.7	-1.0	-0.4	1.4	-1.4	0.0
Col	0.0	1.8	1.2	-0.2	-	-4.0	1.9	0.2	-0.1	-2.4	0.8	-0.6	-1.3	-0.5	1.3	-1.9	0.1
Cri	3.0	4.8	3.7	2.7	2.9	-	4.5	3.1	2.7	0.0	3.6	1.7	1.5	2.3	4.6	1.2	3.1
Dom	-0.6	0.2	-0.3	-0.4	-0.9	-4.0	-	-1.0	-1.5	-2.7	-0.7	-1.5	-1.6	-1.3	0.6	-2.7	-0.7
Ecu	0.4	1.1	0.7	0.1	-0.1	-2.0	0.8	-	-0.3	-1.8	0.1	-1.0	-0.7	-0.4	1.3	-1.3	0.0
Slv	0.7	0.8	0.3	0.1	-0.2	-3.2	0.9	-0.4	-	-3.7	-0.2	-2.2	-0.8	-1.0	1.7	-1.4	-0.1
Gtm	1.1	3.0	2.3	1.4	1.2	-1.7	2.7	1.0	1.9	-	1.8	0.7	-0.1	1.0	2.3	-0.8	1.1
Mex	-0.3	2.9	2.2	-0.3	-0.2	-1.6	2.3	0.1	2.4	0.8	-	1.0	-1.0	-0.1	0.9	-1.8	-0.3
Nic	0.7	1.4	0.9	0.5	0.4	-1.8	1.3	0.3	0.5	-1.2	0.7	-	-0.5	-0.4	1.3	-1.0	0.4
Pan	0.9	5.2	4.3	0.6	1.8	-0.2	4.7	2.2	4.6	2.7	2.3	3.2	-	2.3	2.4	-0.1	1.4
Pry	0.2	1.6	1.2	0.1	0.1	-1.2	1.5	0.2	0.7	-0.4	0.3	0.3	-0.4	-	1.3	-1.1	0.2
Per	-0.7	0.6	0.0	-0.9	-0.9	-1.8	0.2	-0.7	-0.2	-1.2	-0.5	-1.0	-1.3	-0.9	-	-1.7	-1.0
Ury	1.5	5.3	4.4	1.7	2.3	0.5	4.6	2.6	4.8	2.7	2.7	2.8	1.0	2.5	3.4	-	1.9
Ven	0.2	1.8	1.2	0.3	0.1	-1.7	1.4	0.1	0.9	-0.5	0.3	0.1	-0.6	0.0	1.3	-1.2	-

Source: own calculations based on microdata from household surveys.
Note: Table report simulated change in Gini index. Mincer equations estimated using levels of education and Gasparini, Marchionni and Sosa Escudero (2004) procedure for changing educational structure. Workers between 14 and 65.

Table A.4
Change in Gini from microeconometric cross-country decompositions

	Education structure of country…																
Country	Arg	Bol	Bra	Chl	Col	Cri	Dom	Ecu	Slv	Gtm	Mex	Nic	Pan	Pry	Per	Ury	Ven
Arg	-	0.8	-1.0	-0.7	-0.4	-0.6	0.0	0.6	-0.1	-1.8	0.1	-2.1	1.0	-1.0	0.9	-1.0	-0.6
Bol	-1.3	-	-1.2	-2.2	-0.8	-1.2	-0.4	-0.2	-0.3	-1.6	-0.7	-1.9	0.0	-1.7	0.0	-1.8	-1.2
Bra	-0.2	2.3	-	-1.2	0.8	0.4	1.1	1.6	1.8	0.3	1.1	-0.7	1.6	-0.3	2.0	-0.9	0.0
Chl	1.4	0.5	-3.0	-	-1.6	-1.7	-0.3	1.3	-1.4	-5.0	-0.3	-5.4	2.4	-2.9	1.8	-2.0	-1.5
Col	0.4	1.8	-1.2	-1.6	-	-0.9	1.3	2.1	0.3	-4.5	0.5	-4.3	3.1	-1.6	2.4	-1.6	-0.4
Cri	1.7	3.2	-0.4	-0.1	1.0	-	2.6	3.2	1.5	-3.9	1.9	-3.5	4.1	-0.4	3.6	-0.6	0.6
Dom	0.8	0.9	-1.2	-0.2	-0.3	-0.5	-	1.2	-0.4	-3.1	0.2	-3.3	2.0	-1.2	1.5	-0.9	-0.5
Ecu	-0.4	-0.2	-1.8	-1.2	-1.1	-1.2	-0.8	-	-1.0	-3.2	-0.7	-3.3	0.5	-1.8	0.3	-1.6	-1.3
Slv	0.8	1.1	-0.7	-0.9	0.0	-0.5	0.8	1.6	-	-3.4	0.2	-3.1	2.7	-1.2	1.8	-0.8	0.0
Gtm	-0.4	1.8	0.2	-1.3	0.8	0.0	1.1	1.4	1.6	-	0.7	-0.4	1.2	-0.5	1.6	-1.0	0.0
Mex	-1.0	1.1	-0.8	-1.9	-0.1	-0.7	0.3	0.6	0.8	-0.7	-	-1.5	0.7	-1.2	1.0	-1.7	-0.8
Nic	2.6	4.1	1.9	1.4	2.7	2.1	3.4	4.0	3.3	0.2	3.0	-	4.6	1.5	4.3	1.3	2.2
Pan	-1.8	0.8	-1.4	-2.8	-0.7	-1.4	-0.2	0.2	0.3	-1.2	-0.5	-2.1	-	-1.8	0.4	-2.6	-1.5
Pry	0.9	1.9	0.4	0.0	0.9	0.6	1.4	1.7	1.4	-0.3	1.0	-0.6	2.3	-	2.1	0.1	0.6
Per	-0.8	-0.1	-1.6	-1.4	-1.1	-1.2	-0.9	-0.3	-0.8	-2.1	-0.8	-2.4	-0.1	-1.7	-	-1.7	-1.4
Ury	1.0	4.4	1.6	0.0	2.5	1.5	3.1	3.5	3.8	1.8	2.9	0.8	3.1	1.0	4.0	-	1.4
Ven	0.3	1.5	-0.2	-0.4	0.3	-0.1	0.7	1.2	0.8	-0.9	0.6	-1.1	1.5	-0.2	1.5	-0.5	-

Source: own calculations based on microdata from household surveys.
Note: Table report simulated change in Gini index. Mincer equations estimated using years of education and Legovini, Bouillon and Lustig (2004) procedure for changing educational structure. Workers between 14 and 65.