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Human Capital and Income Inequality: Some Facts and Some Puzzles

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Human Capital and Income Inequality: Some Facts and Some Puzzles[†*]

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Abstract

Using an updated data set on human capital inequality for 146 countries from 1950 to 2010, this paper documents several facts regarding the evolution of income and human capital inequality. The main findings reveal that, in spite of a large reduction in human capital inequality around the world, the inequality in the distribution of income has hardly changed. In many regions, the income Gini coefficient in 1960 was very similar to that in 2005. Therefore, improvements in education are not a sufficient condition to reduce income inequality, even though they significantly improve life standards of people at the bottom of the income distribution. We do find evidence that increasing returns to education and exogenous forces such as skill-biased technological progress or globalization have offset the effects of the fall in education inequality, therefore explaining the low correlation between the changes in income and education inequality.

Keywords: education inequality, attainment levels, income distribution, panel data.

JEL Classificaction: I24, O11, O15, O5.

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1. Introduction

In the last few decades, most developing countries have made a great effort to eradicate illiteracy in several hundreds of millions of people. As a result, the inequality in the distribution of education has been reduced by more than half: the average human capital Gini coefficient dropped from 0.55 in 1960 to 0.28 in 2005. However, in spite of the equalizing process in the distribution of education, inequality in the distribution of income has hardly changed. The value of the average income Gini coefficient for the same group of countries was almost equal in 1960 (0.42) as in 2005 (0.41). This trend is not restricted to developing countries alone: in 1960 the human capital Gini coefficient in the high income OECD countries was 0.22 and decreased to 0.15 in 2005, whereas the income Gini coefficient has remained unchanged at 0.30.

This paper analyzes the above evidence in detail and contributes to the literature in several aspects. Firstly, the paper provides the most comprehensive data set on human capital inequality variables, covering 146 countries over a 60-year period. Hitherto, the most comprehensive dataset was that of Castelló and Doménech (2002), which takes the educational attainment levels from Barro and Lee (2001) to compute the Gini coefficient and the distribution of education by quintiles. As Castelló and Doménech (2002) utilize Barro and Lee˙s (2001) data set, the inequality measures are subject to the same criticisms as the average years of schooling. This paper uses the attainment levels by Barro and Lee (2013), which include more countries and years, reduces some measurement errors, and solves some of the shortcomings revealed by De la Fuente and Doménech (2006) and Cohen and Soto (2007). The new inequality indicators are available for 146 countries from 1950 to 2010 in a five-year period and include a total of 1898 observations.

Secondly, using this data set, the paper shows some new, interesting stylized facts regarding the evolution of human capital and income inequality.[1] From 1950 to 2010, there has been a significant reduction in human capital inequality around the world. In most countries, the large reduction of education inequality has mainly been due to the sizeable decline in the share of illiterates. In most advanced countries, however, there is not a clear pattern in the evolution of education inequality, and the human capital Gini coefficient has been mainly determined by the distribution of education among the literate population. For a large sample of countries, the correlation between income and human capital Gini coefficients is low. The average income inequality is greater than that of human capital, whereas its variance is lower. In fact, both across world regions and a large sample

[1] Previous contributions to the literature have found that income inequality is positively correlated to education inequality and negatively related to education (e.g. Becker and Chiswick, 1966, Ahluwalia, 1976). Others, however, found that schooling inequality has a marginal negative, rather than positive, effect on income inequality (Ram, 1984). De Gregorio and Lee (2002) show that, although countries with higher educational attainments and a more equal distribution of education have a more equal distribution of income, a significant proportion of the variation in income inequality remains unexplained.

of countries, income inequality has remained relatively stable over a period of 45 years. Everything included, the evidence shows the reduction in human capital inequality has not been accompanied by declines in the income Gini coefficient. The large expansion in literacy in most developing countries has clearly reached the lowest income groups. As more productive workers will be rewarded with higher wages, we would expect an equalizing process in the distribution of income stemming from the increase in the income at the bottom part of the distribution. Thus, the stability of the income Gini coefficient is puzzling given the large reduction of human capital inequality.

Thirdly, we provide alternative explanations for the low correlation observed between the evolution of human capital and income inequality. A first explanation for the puzzle is that the returns to education are convex. The impact of the distribution of education on income inequality will depend not only on the size of the investments in education but also on the rate of return of these investments. Extensive empirical evidence, based on a Mincer (1974) earning function, shows that highly educated workers earn higher wages on average. Nevertheless, whether the returns increase or decrease with the level of education is still an open debate. The traditional literature suggests the returns decrease with the level of schooling (e.g. Psacharopoulos and Patrinos, 2004). Recent evidence, however, shows that in many countries, the returns to education in the 1990s and 2000s are greater for higher education than for primary schooling (see, for example, Colclough et. al., 2010). If the returns to education are increasing, an extra year of education at the primary level brings a smaller increase in wages than it does at higher levels of education. We test this hypothesis in a sample of 144 countries for the period 1950-2010, and our results reveal that a one-year increment in university is much more productive than a one-year increase in primary education. This evidence is in line with recent studies for individual countries that find returns to education as an explanation for the evolution of income and wage inequality. In the case of China, Ning (2010) documents that increasing returns to education has played a key role in explaining the rapid education expansion and the increment in income inequality. Extensive evidence has been reported for the United States. Goldin and Katz (2007) estimate earnings regressions for 1980 and 2005, showing that rising returns to education have played a key role in explaining the increase in wage inequality in the U.S. This evidence confirms Lemieux's (2006) results, who found that increased returns to post-secondary education accounted for the majority of the increase in wage inequality between 1973 and 2005. The evidence in this paper suggests that increasing returns to education could be a general phenomenon across countries, and an important factor explaining the lack of correlation between human capital and income inequality worldwide.

A second alternative explanation could be that improvements in literacy, which increase the wage of the population at the bottom end of income distribution, have also coincided with an increase of wages in cohorts with higher education, such that all of them maintain their income shares. The latter could be the result of exogenous forces such as globalization (e.g., Goldberg and Pavcnik, 2007) or skill-biased technological progress (e.g., Katz and Murphy, 1992) that have increased wages at the top. Using data on skill premia in a sample of 31 countries from 2000 to 2011, we obtain statistically significant evidence in favor of these hypotheses. We corroborate this result in a broader sample that includes 133 countries in a specification where the dependent variable is the income Gini coefficient. Other things being equal, we find that reductions in inequality in the distribution of education have been accompanied by reductions in inequality in the distribution of income. However, at the same time, we find that a higher demand for skilled workers along with greater trade and financial openness have contributed to the increase in income inequality. On the whole, the evidence indicates that even if there has been an increment in the supply of skills and a reduction in human capital inequality, their effect on income inequality has been offset by the increase in the demand for skilled workers and the effect of globalization.

The structure of the paper is as follows. Section 2 computes the improved measures of human capital inequality and documents some stylized facts about the evolution of human capital inequality. Section 3 analyzes the distribution of income inequality from 1960 to 2005 and shows some disparities when compared with the evolution of human capital inequality. Section 4 analyses some explanations for the lack of correlation between the changes in income and education inequality. Finally, section 5 contains the main conclusions.

2. Evolution of human capital inequality over time

The most comprehensive data set on human capital inequality measures is that of Castelló and Doménech (2002), which takes the educational attainment levels from Barro and Lee (2001) and calculates the Gini coefficient and the distribution of education by quintiles for a large number of countries and periods. However, recent studies have shown that the Barro and Lee (2001) data set suffers from several problems. Cohen and Soto (2007) and de la Fuente and Doménech (2006) illustrate that the data show implausible time series profiles for some countries. Recently, Barro and Lee (2013) have addressed most of these concerns in an improved data set that reduces measurement error and ameliorates the accuracy of the estimates by using more information from census data and a new methodology that makes use of disaggregated data by age group.[2]

[2] The new methodology in Barro and Lee (2013) fills the missing observations by backward and forward extrapolation of the census data on attainment levels by age group with an appropriate lag. It also constructs new estimates of mortality rates and completion ratios by education and age group.

Using the new Barro and Lee (2013) data set and following Castelló and Doménech (2002), we compute the human capital Gini coefficients as follows:

$$Gini^h = \frac{1}{2\overline{H}} \sum_{i=0}^{3} \sum_{j=0}^{3} \left| \widehat{x}_i - \widehat{x}_j \right| n_i n_j \tag{1}$$

where $\overline{H}$ are the average years of schooling in the population 15 years and above, i and j stand for different levels of education, $\widehat{x}$ refers to the cumulative average years of schooling of each level of education, and n are the share of population with a given level of education: no schooling (0), primary (1), secondary (2) and tertiary (3) education.

The new inequality indicators are updated and expanded to 146 countries from 1950 to 2010 in a 5-year span and include a total of 1898 observations. The data set covers most of the countries in the world, including data for 24 advanced economies, 19 countries in East Asia and the Pacific region, 20 countries in East Europe and Central Asia, 25 countries in Latin America and the Caribbean, 18 countries in the Middle East and North Africa, 7 countries in South Asia, and 33 countries in Sub-Saharan Africa.[3]

A comparison between the old and the new human capital Gini coefficient shows that the correlation for the overlapping observations is very high in levels (0.975), but it is low when the variables are measured in a 10-year difference (0.278). This suggests a lower measurement error in the new human capital Gini coefficient derived from a smoother trend in the attainment levels.[4] The attenuation bias in this context is relevant since measurement error is particularly prevalent in the econometric analysis that exploits the within-country variation of the educational data (see Krueger and Lindahl, 2001).

Table 1 shows the summary statistics for the average human capital Gini coefficient for some regions. The data show that the group of countries with the largest human capital inequality is South Asia, with an average human capital Gini coefficient equal to 0.641, followed by Sub-Saharan African (SSA) countries (average $Gini^h$ equal to 0.614), and the Middle East and the North African (MENA) region (average $Gini^h$ equal to 0.575). At the other end, the Eastern European and Central Asian countries (EECA) and the advanced economies are the regions where the average years of schooling are more evenly distributed. In the middle of the extremes, the Latin American and the Caribbean countries (LAC) and the East Asian and the Pacific region (EAP) have average Gini coefficients of 0.338 and 0.385, respectively.

In spite of the large differences in the distribution of education across regions, there has been a general reduction of human capital inequality worldwide. Table 1 shows the

[3] We have followed the same classification of countries as in Barro and Lee (2013).

[4] Barro and Lee (2013) also find that the old and the new measures of the average years of schooling are highly correlated in levels and there is little relationship when the variables are measured in differences.

Table 1
Summary Statistics

	$Gini^h$										
	Countries	*Mean*	*Std. Dev.*	*Min*	*Max*	$Gini^h_{1950}$	$Gini^h_{2010}$	$3^{rd}Q^h_{1950}$	$3^{rd}Q^h_{2010}$	$1^{st}/5^{th}Q^h_{1950}$	$1^{st}/5^{th}Q^h_{2010}$
World	146	0.412	0.251	0.026	0.997	0.557	0.257	0.202	0.420	0.096	0.278
Advanced	24	0.212	0.116	0.049	0.827	0.242	0.156	0.425	0.499	0.371	0.421
EAP	19	0.385	0.193	0.097	0.923	0.588	0.230	0.159	0.448	0.009	0.262
EECA	20	0.207	0.124	0.026	0.611	0.331	0.099	0.370	0.541	0.173	0.579
LAC	25	0.338	0.169	0.048	0.915	0.456	0.217	0.269	0.457	0.059	0.309
MENA	18	0.575	0.241	0.145	0.997	0.808	0.313	0.046	0.385	0.001	0.133
South Asia	7	0.641	0.227	0.150	0.988	0.780	0.414	0.061	0.279	0.000	0.049
SSA	33	0.614	0.219	0.128	0.963	0.798	0.407	0.027	0.296	0.000	0.105

value of the Gini coefficient for each region in 1950 and in 2010. The numbers illustrate that in most of the regions, the decline has been spectacular, and the Gini coefficients have been reduced by more than half. To analyze whether the reduction in education inequality has been due to variations at the bottom, middle, or upper part of the distribution, Table 1 also displays the values of the 3^{rd} quintile and the ratio between the bottom and the top quintile.[5] The data show a general increment in the share of education going to the third quintile and a general increase in the ratio of the bottom to the top quintile as well, suggesting that the improvement in equality has mainly benefited the lowest part of the distribution.

Certainly, a further examination of the data reveals that the large reduction of education inequality has mainly been due to a sizeable decline in illiteracy. Figure 1 displays the evolution over time of the population 15 and above who are illiterate. Without exception, the figure shows that all the regions in the world have experienced a great reduction in the share of illiterates that has implied a decline by more than half in the population with no education. Interestingly, Figure 2 plots a similar decline in the human capital Gini coefficient over time. The comparison of both figures indicates the evolution of the share of illiterates and the Gini coefficient is almost identical, suggesting the reduction in the Gini coefficient over time has been determined, to a great extent, by the decline in the share of illiterates.

This fact can be explained by the weight of the share of illiterates in the computation of the human capital Gini coefficient. To illustrate this point, we reorganize eq. (1) as follows:[6]

$$Gini^h = n_o + \frac{n_1(n_2x_2 + n_3(x_2 + x_3)) + n_2n_3x_3}{\overline{H}} \tag{2}$$

Thus, the Gini coefficient of education is a proportional measure of the share of illiterates in the society. A great reduction in the share of illiterates will translate into a similar reduction in the Gini coefficient. Whether the reduction in the Gini coefficient is greater or lower than that in the share of illiterates will depend on the changes in the distribution of education among the literates. Given that:

$$Gini^{LIT} = \frac{1}{2\overline{H}^{LIT}} \sum_{i=0}^{3} \sum_{j=0}^{3} \left| \widehat{x}_i - \widehat{x}_j \right| n_i^{LIT} n_j^{LIT} \tag{3}$$

[5] We compute the bottom to the top quintile as a measure of equality, instead of the top to the bottom quintile as a measure of inequality, since in many countries more than 60 percent of the population were illiterate and the value of the third quintile in that case is equal to zero.

[6] x_i is the average years of schooling of each education level, and the cumulative average years of schooling are computed as: $\widehat{x}_0 \equiv x_0 = 0$, $\widehat{x}_1 \equiv x_1$, $\widehat{x}_2 \equiv x_1 + x_2$, $\widehat{x}_3 \equiv x_1 + x_2 + x_3$.

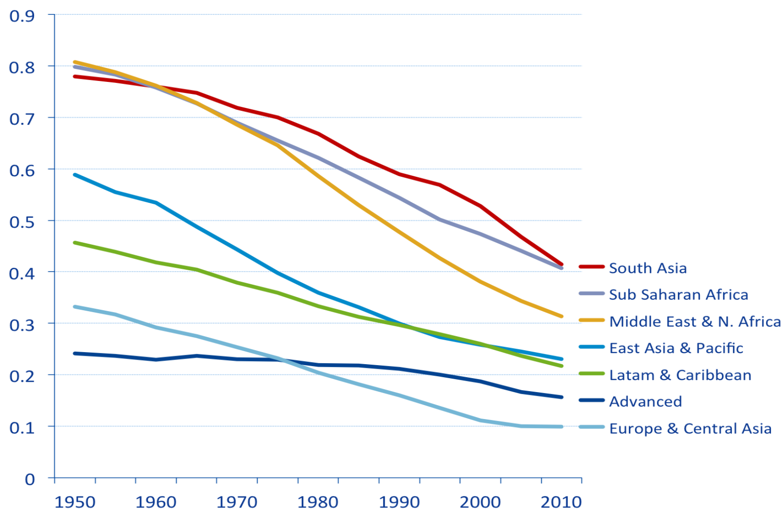

Figure 1: *Human Capital Gini Coefficient of population 15+.*

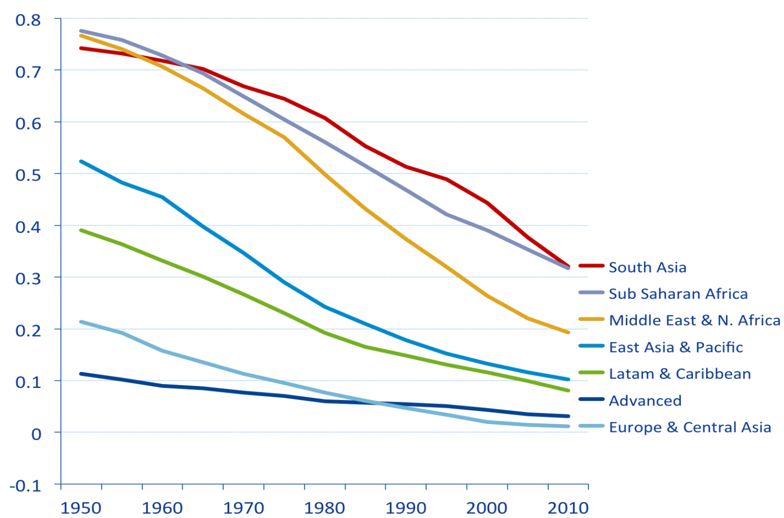

Figure 2: *Share of illiterates of population 15+.*

where $Gini^{LIT}$ is the human capital Gini coefficient among the literates, $n_i^{LIT} = n_i/(1-n_0)$ and n_0 is the share of population with no education, eq. (3) can be rewritten as follows:

$$Gini^{LIT} = \frac{1}{(1-n_0)} * \frac{n_1(n_2x_2 + n_3(x_2+x_3)) + n_2n_3x_3}{\overline{H}} \tag{4}$$

Then, the human capital Gini coefficient can be formally decomposed as a combination of the share of illiterates and the Gini coefficient among the literates in the following way:

$$Gini^h = n_0 + (1-n_0)Gini^{LIT} \tag{5}$$

As corroborated by the empirical evidence, when the share of illiterates is very high, the evolution of the human capital Gini coefficient is mainly determined by the share of illiterates. On the other end, when the share of illiterates is almost zero, the distribution of primary, secondary and tertiary education is what determines the evolution of education inequality. This evidence is illustrated in Figure 3, which plots the relationship between the changes in the distribution of education and the changes in the share of illiterates for the whole sample of countries from 1950 to 2010. The figure shows that in countries where in 1950 the share of illiterates was high, the reduction in the Gini coefficient has been very similar to that of the reduction in share of illiterates, since most of the countries are located close to the diagonal line. Countries such as Bahrain, Botswana, Kenya or Uganda, among others, have experienced an important increase in the literacy rates and, as a result, in 2010 the share of illiterates was below 30 percent and the Gini coefficient was also below 0.3. On the other extreme, however, there are countries where the increment in the literacy rates has been more moderate. For instance, in Niger, Mozambique, Gambia, Mali or Sierra Leone the share of illiterates in 2010 was still above 60 percent, and the Gini coefficient was above 0.6 as well.

Nevertheless, for those countries where most of the population was literate in 1950, there is a slight variation in the share of illiterates and a larger variance in the changes of the Gini coefficient. Figure 4 displays the absolute change in the Gini coefficient and the share of illiterates in the high-income OECD economies. With the exception of Spain, Portugal, Greece, Cyprus and Korea, which also had a substantial population that were illiterate in 1950 and have reduced both illiteracy and education inequality over time, we observe a small reduction in the share of illiterates and a considerable difference in the evolution of education inequality across countries. For instance, countries such as Finland, Iceland, the Netherlands, Austria or UK show an increase in the human capital Gini coefficient over time, whereas the inequality in the distribution of education decreased in Sweden, Canada, USA, Australia, and Germany.[7]

[7] The figure also shows that in some developed economies, the change in the share of illiterates is positive

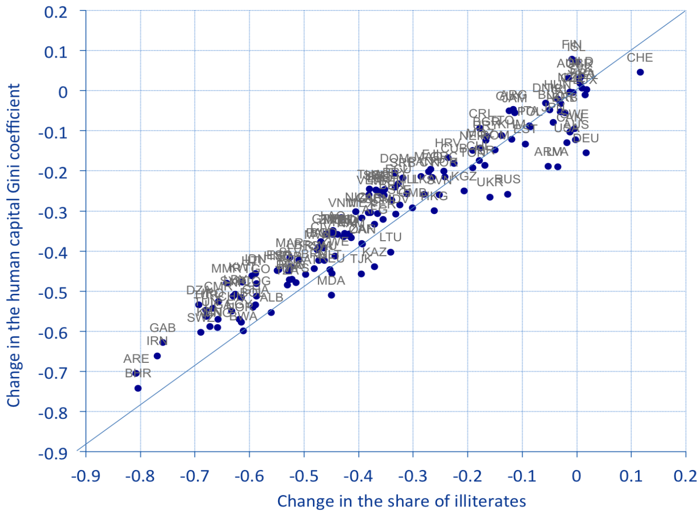

Figure 3: *Change in the human capital Gini coefficient and in the share of illiterates, 1950-2010.*

Figure 4: *Change in the human capital Gini coefficient and the share of illiterates. High-income OECD countries, 1950-2010.*

Taken together, we can compile the key results on the evolution of human capital inequality over time in the following stylized facts. First, from 1950 to 2010 there has been a significant reduction in human capital inequality around the world. Second, in most countries the large reduction of education inequality has mainly been due to the sizeable decline in the share of illiterates. Third, in most advanced countries there is not a clear pattern in the evolution of education inequality, and the human capital Gini coefficient has been mainly determined by the distribution of education among the literates.

3. Human Capital and Income Inequality

In this section, we analyze to what extent the reduction in human capital inequality, explained in most countries around the world by the increase in literacy, has affected the distribution of income inequality.

We start by comparing the mean values of the human capital and income Gini coefficients for those countries for which income inequality data are available. We measure income inequality through the net income Gini coefficient taken from the Standardized World Income Inequality Database (SWIID), version SWIID v3.0, which uses a custom missing-data algorithm to standardize WIID from the LIS dataset.[8] The data include 75 countries with observations from 1960 to 2005. Table 2 displays the mean values of the income and human capital Gini coefficients for several regions in the world. The table illustrates two main features.

Firstly, if we compare the average value of the income ($Gini^y$) and the human capital ($Gini^h$) Gini coefficients, we observe that the countries with the highest and the lowest inequality in the distribution of income and education do not coincide. The most remarkable example is that of Latin America and the Caribbean, which is one of the regions with the highest income inequality and a moderate inequality in the human capital distribution. At the other extreme, countries in South Asia display high inequality in the distribution

(e.g. Belgium, France, Germany, the Netherlands, Switzerland and Great Britain). This fact is surprising since the tendency worldwide has been the elimination of illiteracy, and we do not find any developing country in which the share of population with no education has increased. A plausible explanation for the increment in the population with no education could be that some new immigrants in the developed countries are illiterate.

[8] Most of the studies that have analyzed the determinants and the effects of income inequality have used the UNU/WIDER-UNDP World Income Inequality Database (WIID), which is an updated version of Deininger and Squire's (1996) data set and reports income inequality measures for developed as well as developing economies. However, data on income inequality that includes several countries have been an issue of concern due to their low quality and related problems of comparability across countries and the scarcity of coverage across countries and over time (e.g. Atkinson and Brandolini (2001)). The most reliable dataset on income inequality is the Luxemburg Income Study (LIS) that provides improved data for income inequality measures in terms of their quality and comparability across countries. Nevertheless, the main drawback of the LIS data set is that it only contains data for a reduced sample of advanced economies starting mainly in 1980, which reduces the sample size considerably.

Table 2
Summary Statistics

	Countries	$Gini^h$	$Gini^h_{1960}$	$Gini^h_{2005}$	$Gini^y$	$Gini^y_{1960}$	$Gini^y_{2005}$
World	75	0.352	0.454	0.243	0.373	0.381	0.379
Advanced	22	0.212	0.233	0.160	0.294	0.307	0.308
East Asia and the Pacific	9	0.341	0.524	0.225	0.377	0.397	0.382
Europe and Central Asia	6	0.139	0.181	0.085	0.247	0.241	0.293
Latin America and the Caribbean	15	0.300	0.388	0.214	0.470	0.481	0.463
Middle East and North Africa	7	0.582	0.794	0.358	0.395	0.397	0.384
South Asia	4	0.578	0.698	0.411	0.330	0.321	0.371
Sub-Saharan Africa	12	0.577	0.744	0.399	0.478	0.461	0.448

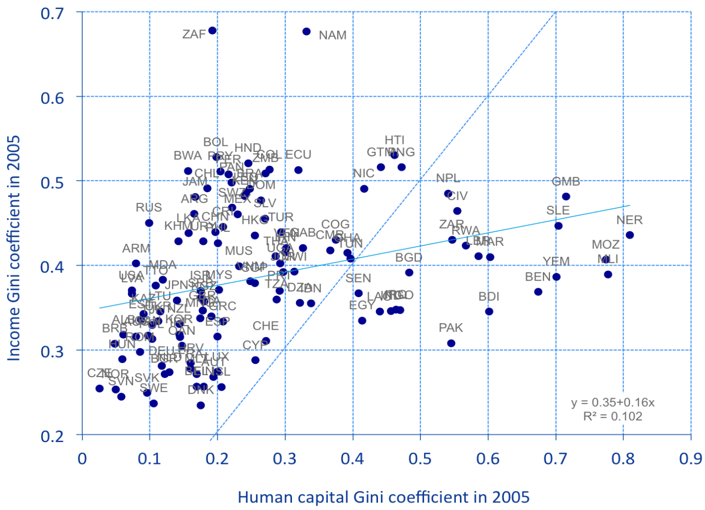

Figure 5: *Human capital and income Gini coefficients across countries in 2005.*

of education and a relative low inequality in the distribution of income. We get a similar picture when we look at a large cross-section of countries, as in Figure 5, which shows the correlation between the income and the human capital Gini coefficients in 2005. Several key points emerge from this figure. First, in most countries, income inequality was greater than human capital inequality. Thus, only 21 of 75 countries are below the diagonal representing equal values for human capital and income Gini coefficients. Second, the variance in education inequality is higher than in income inequality. The income Gini coefficient in 2005 takes values between 0.235 and 0.678, whereas the minimum and maximum values of the human capital Gini coefficient are 0.026 and 0.809, respectively. Most of the countries with the highest income inequality are located in Latin America, and those with the highest education inequality are in Africa and South Asia. On average, the advanced economies have the lowest inequality in the distribution of education and income. However, there are some advanced economies, such as USA or Japan, with income Gini coefficients higher than those in India, Pakistan and Egypt. Third, the correlation between the income and the human capital Gini coefficients is not very high (0.344).

In the second place, education and income inequality have evolve in a different manner. The last two columns of Table 2 display the values of the income Gini coefficient at the beginning and at the end of the sample period. The data indicate that the income Gini coefficient has remained quite stable over a period of 45 years. This evidence is illustrated in Figure 6, which plots the evolution of the income Gini coefficient for all the regions and available time periods. An interesting feature is that, in spite of some variations over short periods of time, in most of the regions the income Gini coefficient in 2005 was very similar to that in 1960, reflecting the long-term stability of the income Gini coefficient, despite the significant reduction in human capital inequality. While Figure 1 shows a notorious reduction of education inequality over time, mainly due to a reduction of the illiterate population (Figure 2), Figure 6 indicates the inequality in the distribution of income has scarcely changed.

This evidence is corroborated in Figure 7, which highlights the absence of correlation between the change in income and human capital Gini coefficients in a sample of 75 countries from 1960 to 2005. Even though there are some countries in which both income and education inequality have increased (e.g., New Zealand, Great Britain and the Netherlands) and others where both variables have decreased (e.g. Kenya, Taiwan, Senegal or Colombia, among others), in a large number of countries changes in income and education inequality display a non-significant correlation. For example, in countries such as China, India, Singapore, USA, Argentina, Australia and many others, there has been a reduction in the inequality of education distribution and an increase in the inequality of income distribution. On the contrary, in Austria, Finland and France, the inequality in the distribution of education has increased and income inequality has been reduced.

A plausible explanation for this fact is that the reduction in the number of illiterates and, therefore, in education inequality, has reduced income inequality by increasing the income at the bottom quintile. At the same time, however, other factors might have raised income inequality by increasing the share of income accruing to the top quintile.[9] As a result, the overall income inequality, measured through the income Gini coefficient, could have remained quite stable. In the Appendix, we display some evidence that shows this has not been the case.

In sum, the past decades have witnessed a large decline in education inequality, driven by the decrease in the illiterate population, which has not been accompanied by similar reductions in income inequality. This section has presented extensive evidence suggesting that the correlation between the evolution of income and education inequality across countries and over time is weak. We can summarize the main findings in the following stylized facts. First, for a large sample of countries, the correlation between income and human capital Gini coefficients is low. The average of income inequality is larger than that of human capital, whereas its variance is lower. Second, both across world regions and a large sample of countries, income inequality has remained relatively stable over a

[9] Atkinson et al. (2011) show that in the second half of the twentieth century, many countries have experienced an increase in the top income shares. The degree of the increment has varied dramatically across countries. Among the 22 countries for which there are available data, Western English-speaking countries, China and India, and to a lesser extent, Southern European and Nordic countries, display a substantial increase in the top income shares in the last decades, whereas there is no increase or a modest one in Continental Europe (France, Germany, Netherlands, Switzerland) and Japan.

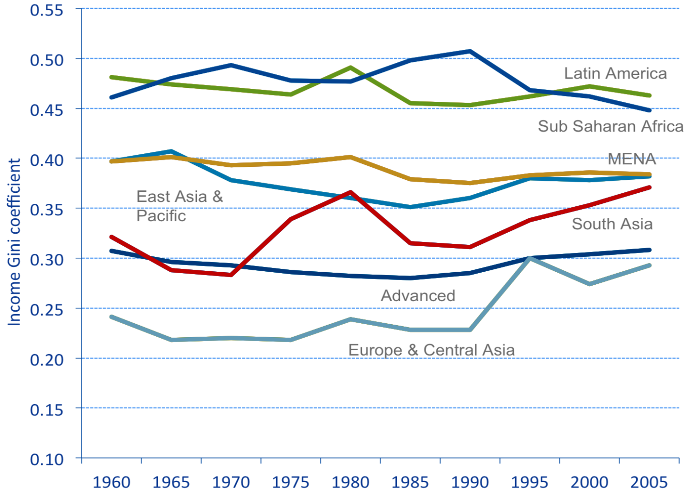

Figure 6: *Evolution of the income Gini coefficient across regions, 1960-2005.*

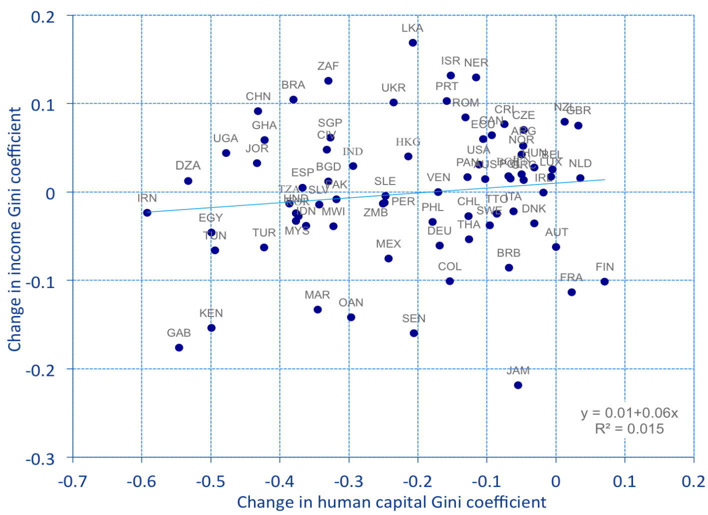

Figure 7: *Change in income and human capital Gini coefficients across 75 countries, 1960-2005.*

period of 45 years. Third, reductions in human capital inequality have not been accompanied by declines in the income Gini coefficient.

4. Explanations for the low correlation between changes in income and education inequality

The stability of the income Gini coefficient and the weak correlation between changes in the distribution of human capital and income are puzzling facts given the large reduction of human capital inequality over time. Ceteris paribus, one should expect that a large decline in human capital inequality would translate into a decline in income inequality as well. In this section, we consider potential explanations as to why income inequality has not decreased.

4.1 Increasing returns to education

Relative low returns in primary education in relation to secondary or tertiary education could explain why, in spite of the observed reduction in the share of illiterates, there is not an increase in the income of the bottom quintiles. In fact, the effect of a more equalitarian distribution of income, derived from an increment at the lower levels of schooling, may be diluted if the returns to education are convex. The intuition behind this potential explanation is displayed in Figure 8. In this example, an individual (or quintile) with no education in t becomes educated in $t+1$. At the same time, human capital at the top of the distribution also increases, but at a much more moderate rate than at the bottom, reducing human capital inequality. However, the presence of increasing returns to scale may give way to a similar increase in their returns, such that income inequality remains almost unchanged.

Given the lack of homogenous microeconomic data for a large panel of countries, we test this potential explanation using aggregate international data. In particular, we examine this hypothesis by estimating an aggregate production function of the form:

$$Y = AK^{\alpha}(hL)^{1-\alpha} \tag{6}$$

where Y is aggregate income, A stands for total factor productivity, K is the aggregate stock of physical capital, h refers to the human capital per worker, and L is the total number of workers. Rewriting the expression in per worker terms yields

$$Y/L = A(K/L)^{\alpha}h^{1-\alpha} \tag{7}$$

Following the literature on the private returns to education, the simplest macro specification of a Mincerian human capital production function can be written as follows:

$$h = e^{\theta S} \tag{8}$$

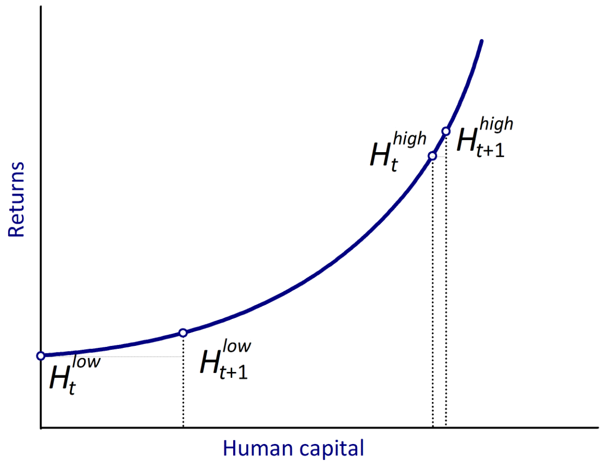

Figure 8: *Increasing returns to education and human capital*

where S are the average years of schooling in the workforce and θ is the return to education. Taking logs in equation (8) yields

$$\ln y = \ln A + \alpha \ln k + (1-\alpha)\theta S \tag{9}$$

We can decompose S as the addition of the average years of schooling of different levels of education

$$S = S^{PRIM} + S^{SEC} + S^{TERT} \tag{10}$$

Thus, the aggregate returns to primary, secondary, and university can be computed by estimating the following specification:

$$\ln(y_{i,t}) = \beta_0 + \beta_1 \ln(k_{i,t}) + \beta_2 S_{i,t}^{PRIM} + \beta_3 S_{i,t}^{SEC} + \beta_4 S_{i,t}^{TERT} + \gamma_i + \delta_t + \mu_{i,t} \tag{11}$$

where $y_{i,t}$ is real GDP per worker in country i measured at year t, $k_{i,t}$ is the stock of physical capital per worker, S^{PRIM}, S^{SEC}, S^{TERT} are the average years of schooling for the population 15 years and above in primary, secondary and tertiary education, δ_t is a time-specific effect, γ_i stands for specific characteristics in every country that are constant over time and $\mu_{i,t}$ collects the error term that varies across countries and across time. The results of the estimation of this specification would essentially establish that more education is good (if $\widehat{\beta}_i > 0$) and which education level is most productive. For example, returns to education are convex when $\widehat{\beta}_4 > \widehat{\beta}_3 > \widehat{\beta}_2$.

Table 3 displays the results of estimating equation (11) under different assumptions regarding the error term. Column (1) assumes that $\gamma_i = 0$ and reports the OLS estimates. Results suggest all levels of education are productive; the estimated coefficients are positive and statistically significant at the 1 percent level for primary, secondary and tertiary education. The evidence also indicates the returns to education are increasing with the level of schooling; one year increment in university is almost ten times more productive than the increase in one year in primary education.

Although this preliminary evidence is suggestive, OLS estimates may be biased since they fail to control for specific characteristics of countries that scarcely change over time. We can control for country specific effects by assuming that $\gamma_i \neq 0$. Results with the Fixed Effect (FE) estimator, reported in column (2), show the coefficients retain the convex effect of the different levels of education. As an alternative estimation, we also control for unobservable heterogeneity by estimating eq. (11) in first differences. It is worth noting, however, that by taking first differences most of the variation in the data, which comes from variability across countries, disappears. This fact may indeed increase the measurement error bias by increasing the variance of the measurement error relative to the variance of the true signal (Griliches and Hausman, 1986). Column (3) reports the results for the 10-year increments, and column (4) displays the long-term difference over a period of 60 years.[10] The results show the coefficient of the average years of university education remains positive and higher than that of the secondary education, whereas that of the primary schooling is even negative in some specifications.

Another concern is the endogeneity of education. We test the robustness of the results by using instrumental variables. We use the parents' education as instruments for the years of schooling. Specifically, we use the average years of schooling in primary, secondary, and university of the population 40-74 years old. The identification strategy assumes that parents' education is highly related to their offspring's education, and that income at year t is very unlikely to determine the years of schooling of the population that studied about 19 and 68 years back.[11] In line with the previous estimates, the results with instrumental variables, displayed in columns (5-8), show the coefficients of the educational variables are positive and increasing with the level of education.

Although the results may still be driven by some other omitted variables and affected by multicollinearity and, therefore, should be interpreted with caution, different econometric techniques point to a convex relationship between the aggregate level of output per worker and the years of schooling in primary, secondary, and university education.

[10] When data in 1950 or 2010 is missing, we replace the gap with the first and the last available observation.

[11] For example, assuming that the population starts primary education at 6 years of age and finishes tertiary education at 21 years of age, implies that population 40 years old started primary education in $t-34$ and finished tertiary education in $t-19$. Likewise, population 74 years old started primary education in $t-68$ and finished tertiary education in $t-53$.

In all specifications, the estimated coefficient of the average years of primary education is lower than that of any other level of schooling and, in some regressions, it is even negative. These results suggest that increasing returns to education could be the reason why the change in the income Gini coefficient and the global reduction of education inequality do not correlate.

Explanations for the increasing returns of education found in many countries have mainly focused on the U.S. economy. Autor et al. (2006) have proposed that the polarization of wages, observed since the 1990s in the U.S., can be accounted for by computers and other new technologies that substitute labor in routine tasks. Other papers suggest that skill mismatch can explain the increase in earnings inequality in the United States during the period 1973-2002 (e.g., Slonimczyk, 2013).

4.2 Skill-biased technological change and globalization

An alternative explanation for the long-term stability of income inequality could be that, despite the increase in the supply of educated workers, the demand for skills has kept pace with the human capital investment, so that wage dispersion has remained unchanged in the long term. The reasoning behind this potential explanation is represented in Figure 9. In this example, an individual (or quintile) with no education in t becomes educated in $t+1$. However, the increase in their income is the same as for an individual with high education, who benefits from the increase in wages due to skill-biased technological change. As a result, although there is a reduction in human capital inequality, income inequality remains unchanged.

The ˇcanonical modelı of the race between education and technological change (e.g., Katz and Murphy, 1992, Card and Lemieux, 2001, or Acemoglu and Autor, 2012, among others) provides a well-founded explanation of the effects of skill-biased technological change. The motivation behind this literature is the observation that in the United States and other developed countries, in spite of the increment in the supply of college graduate workers, there has been an increase in wage inequality, proxied by the increase in the wage of college graduate workers relative to the wages of high school graduates. This model argues that the returns to skills are determined by a race between the demand of skills, influenced by a skill-biased technological change, and the increase in the supply of skills. When the relative demand increases faster than the relative supply, wage dispersion rises. On the contrary, when the supply outpaces the demand, wage dispersion decreases.

Although the evidence shows that the ratio of skilled to unskilled workers has increased not only in the high-income OECD countries but also in the less developed economies, it is difficult to perform a proper test of this model for a large sample of countries

Table 3

Dependent variable: log of output per worker

	OLS	*FE*	*First Dif 10-year*	*First Dif 1950-2010*	*Instrumental Variables* *OLS*	*FE*	*First Dif 10-year*	*First Dif 1950-2010*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(K/L)_t$	0.706[a]	0.518[a]	0.439[a]	0.530[a]	0.693[a]	0.451[a]	0.278[a]	0.521[a]
	(0.015)	(0.015)	(0.027)	(0.054)	(0.015)	(0.024)	(0.054)	(0.054)
S_t^{PRIM}	0.029[a]	-0.024[c]	-0.045[b]	0.010	0.040[a]	0.043[b]	0.038	0.066
	(0.010)	(0.013)	(0.018)	(0.036)	(0.011)	(0.021)	(0.031)	(0.045)
S_t^{SEC}	0.041[b]	0.064[a]	0.046[a]	0.058	0.093[a]	0.098[a]	0.054[b]	0.069
	(0.020)	(0.015)	(0.018)	(0.040)	(0.018)	(0.021)	(0.026)	(0.051)
S_t^{TERT}	0.273[a]	0.143[b]	0.175[c]	0.251	0.126	0.217[b]	0.223[c]	0.395[b]
	(0.095)	(0.062)	(0.090)	(0.158)	(0.089)	(0.024)	(0.124)	(0.185)
Constant	1.925[a]	3.743[a]	0.178[a]	0.089	2.080[a]	4.328[a]	0.210[a]	-0.110
	(0.144)	(0.143)	(0.018)	(0.178)	(0.137)	(0.263)	(0.034)	(0.207)
R^2	0.874	0.764	0.410	0.646	0.905	0.698	0.359	0.638
Obs.	1514	1514	1226	122	1226	1226	938	122
Countries	144	144	144	122	144	144	134	122
Country dummies	NO	YES	YES	YES	NO	YES	YES	YES
Time dummies	YES	YES	YES	NO	YES	YES	YES	NO

Notes: Robust Standard errors in parenthesis. a, b, and c are 1, 5, and 10 per cent significance level. The dependent variable is the log of the real GDP per worker. The explanatory variables are the log of the capital stock per worker and the average years of primary, seconday, and university education of the population 15 years and above. The years of education are instrumented in columns (5-8). The instruments for the average years of schooling in primary, secondary and university are the corresponding average years of schooling of each educational level among the population 40-74 years. The instrument for the stock of capital is the stock of capital lagged 10 years.

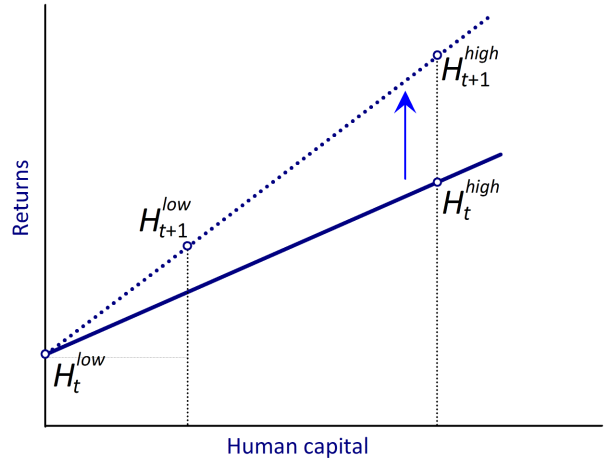

Figure 9: *Skill-biased technological change and human capital*

and decades, as the one used in the previous section, since there is not such a large sample of data for workers with different levels of education.[12] For this reason, we rely on the information provided by the OECD in Education at a Glance (2013) to test the canonical model of the race between education and technological change in a sample of 31 countries from 2000 to 2010, which includes some emerging countries such as Brazil, Turkey, and Korea. The evidence presented in Figure 10 for the sample average is consistent with the skill-biased technological change. Despite the increase of adult population with tertiary education, with respect to those with low secondary education, relative earnings have increased almost 30 percent in just ten years, from 1.85 to 2.35.

Following the seminal work of Katz and Murphy (1992), we relate the earning gap or skill premium (i.e., the wage ratio of skilled and unskilled workers w_{H_t}/w_{L_t}) to the relative supply of skills (H/L) and the relative technology trend (A_H/A_L), proxied by a time trend (t):[13]

$$\ln(\frac{w_{H_t}}{w_{L_t}}) = \frac{\sigma - 1}{\sigma}\gamma_0 + \frac{\sigma - 1}{\sigma}\gamma_1 t - \frac{1}{\sigma}\ln(\frac{H_t}{L_t}) \tag{12}$$

[12] Using data of the attainment levels by Barro and Lee (2013), in the advanced economies, the ratio of the share of population that has completed tertiary education to the share of population that has completed only primary has increased from 0.069 in 1950 to 2.592 in 2010. In this group of countries, the standard deviation in 2010 was very large (3.842) with a minimum value of 0.081 in Portugal and a maximum value of 15.412 in the U.S. In the less developed countries, the increment has been lower, although important in quantitative terms; the ratio increased from 0.108 in 1950 to 0.632 in 2010.

[13] It is common in the literature to assume that there is a log-linear increase in the demand for skills over time coming from technology, captured as follows:

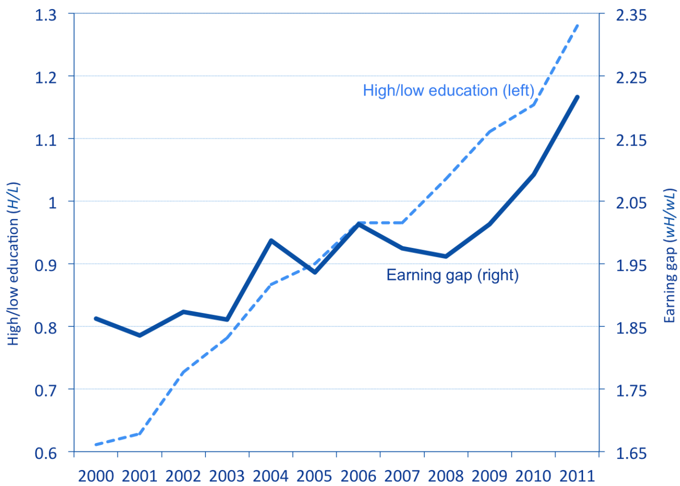

Figure 10: *Relative supply of population with high education with respect to population with low secondary education (left axis) and the earning gap (right axis). Average for the OECD, 2000-2011.*

where σ is the elasticity of substitution between high skill and low skill labor, H refers to the share of population 25-64 years old with tertiary education, and L is the share of population with education below upper secondary.

The estimated coefficients for an unbalanced sample of 31 countries from 2000 to 2011 (214 observations) are displayed in Table 4. In the first column, we include time dummies for each year from 2000 to 2011. As we can see, the relative supply H/L enters with the correct sign. The elasticity of substitution between population with tertiary education and those below upper secondary is about 9.26 ($\sigma = 1/0.108$). We cannot reject the hypothesis that the time effects are well approximated by a time trend which is statistically significant as shown in column (2). The coefficient of the time trend is 0.021; that is, the earning gap has increased on average 2.1 percent each year (23 percent from 2000 to 2011). This result is relatively robust to the inclusion in column (3) of two sets of countries' dummies, which are statistically significant. In Figure 11, we plot the skill premium for the sample average and the fitted values obtained with the coefficients estimated in column (2), showing that the model is able to explain a large part of the increasing earning gap during this period.

$$\ln(\frac{A_{H,t}}{A_{L,t}}) = \gamma_0 + \gamma_1 t$$

Table 4
Dependent Variable: $\ln \frac{w_H}{w_L}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln \frac{H}{L}$	-0.108^a	-0.108^a	-0.206^a	-0.221^a	-0.231^a	-0.252^a
	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)	(0.029)
t		0.021^a	0.027^a	0.024^a		
		(0.006)	(0.005)	(0.005)		
$\ln \frac{X+M}{GDP}$				0.155^a		0.175^a
				(0.046)		(0.041)
$\ln \frac{FA+FL}{GDP}$				-0.051^a		-0.080^a
				(0.015)		(0.018)
$\ln \frac{X^{high}}{X}$					0.094^a	0.127^a
					(0.025)	(0.024)
R^2	0.135	0.131	0.358	0.414	0.407	0.492
Obs.	214	214	214	214	214	214
N	31	31	31	31	31	31
δ_t	Y	N	N	N	Y	Y

Notes: OLS Regression. Robust standard errors in parenthesis. a, b and c are 1, 5, and 10 percent significance levels respectively. Regression from 2000 to 2011. Columns (3-6) include two set of dummies: one for the USA and other for IRE, ITA, ESP and TUR.

Although the estimated equation in Table 4 is obtained from models of skill-biased technological change, it could also be possible that the coefficient of the time trend reflects other factors behind the increase in the earning gap, such as the effects of globalization (OECD, 2011). In all cases, an increasing inequality in the earning gap between the population with high and low education could have offset the reduction of human capital inequality. In column (4), we show that the coefficient of the time trend is still significant after the inclusion of variables that approximate the effect of globalization. In particular, when we add a measure of trade openness (exports plus imports as a share of GDP, $(X + M)/GDP$, taken from the PWT 7.1), and an indicator of financial openness (the ratio of gross stocks of foreign assets and liabilities to GDP, $(FA + FL)/GDP$, taken from Lane and Milesi-Ferretti, 2007) to the set of controls, the coefficient of the time trend is slightly lower but continues being positive and statistically significant at the 1 per cent level. The estimated coefficients of the variables that measure globalization indicate two differing effects: whereas more trade openness is associated with a higher skill premium, more financial openness is negatively related to wage inequality.

To check for the robustness of the results to alternative indicators for the demand for skilled labor, in columns (5) and (6) we replace the time trend with the share of high-technology exports in total manufactured exports (X^{high}/X), taken from the World Development Indicators. We expect that a greater production of high technology goods is likely to increase the demand for high-skill labor. The effect is statistically significant: the results show that a higher share of exports in high-technology goods and services is related to a

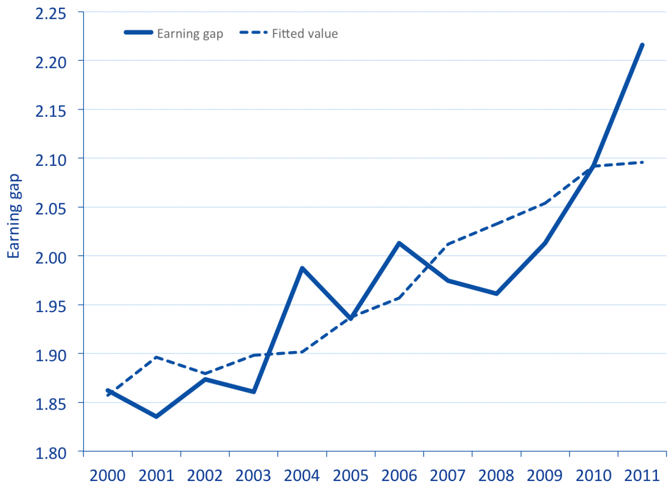

Figure 11: *Average skill premium in the OECD, 2000-2011.*

higher skill premium.

These results suggest that skill-biased technological change and globalization are mechanisms that affect the skill premium. However, as most of the reduction in education inequality has been as a consequence of the effort to eradicate illiteracy, we would like to explore whether these results hold in a sample that also includes the less developed countries. As stated before, the problem is that there are not data available on skill premium for a broad number of countries and periods. As an alternative, we explore the role of these channels by analyzing their effect on income inequality directly. For this purpose, we estimate the following equation:

$$\ln Gini^{Y}_{i,t} = \alpha_0 + \alpha_1 t + \alpha_2 \ln(H^{TERT}/H^{PRIM})_{i,t} + \alpha_3 \ln\left(\frac{X+M}{GDP}\right)_{i,t} + X\beta + \delta_i + \varepsilon_{i,t} \quad (13)$$

We measure the relative supply of skills as the ratio of the average years of tertiary to primary education in the population 15 years old and above $\ln(H^{TERT}/H^{PRIM})$, as in most developing countries unskilled workers have attended at the most primary schooling. According to models of skill-biased technological change, we would expect that $\alpha_1 > 0$ and $\alpha_2 < 0$. Goldberg and Pavenic (2007) survey the literature on the effect of globalization on income inequality for individual countries and the results suggests that $\alpha_3 > 0$. Epifani and Gancia (2008) also show that increases in market size, proxied by measures of country size and trade openness, lead to higher returns to education, skill premia and income inequality.[14] As in Table 4, we also include financial openness in the set of controls.

It is important to note that the large stability of the income Gini coefficient in the long term suggests the variability of the income Gini is mainly cross-sectional. The R^2 is equal to 0.86 in a regression where the dependent variable is the income Gini coefficient and the explanatory variables are country dummies, whereas the R^2 is 0.01 in a similar regression where the explanatory variables are time dummies. These results confirm that most of the variability in the income Gini coefficient comes from variability across countries. Thus, econometric techniques that exploit the cross-sectional or the within country variation in the data may give different results.[15] To analyze both cases, we first estimate equation (1) assuming that $\delta_i = 0$. The advantage of this assumption is that we can use econometric techniques that exploit the whole cross-country variation in the data. The problem, however, is that the omission of time invariant country-specific characteristics may bias the estimated coefficients. On the contrary, if we assume that $\delta_i \neq 0$, and estimate a fixed effect model, we can control for unobservable heterogeneity but at the expense of the very low within-country variation in the income Gini coefficient.

The results of estimating equation (13) in both specifications are displayed in Table 5. The sample includes an unbalanced panel of 133 countries with observations from 1960 to 2010. Results for the OLS estimates, which assumes $\delta_i = 0$, are displayed in columns (1) to (6). In line with the predictions of the ˇcanonical modelı of the race between education and technological change, column (2) shows the coefficient of the supply of relative skills is negative, the coefficient of the time trend is positive and both are statistically significant at the 1 percent level. As stated in column (3), the results do not change when we control for globalization variables.

According to the influential work by Kuznets (1955), inequality in the distribution of income increases and later decreases as per capita income rises.[16] Thus, the relative supply of skills could be picking up the countries˙ levels of development or the influence of the distribution of education on income inequality. To mitigate concerns of omitted vari-

[14] Jaumote et al. (2013) find that trade globalization is associated with a reduction in income inequality, whereas financial globalization is associated with an increase in inequality.

[15] While human capital inequality data might have enough signal in both cross-section and panel data models, the stability of the income Gini coefficient could explain the mixed evidence found in the literature that analyses the effect of income and human capital inequality on economic growth. Whereas cross-section estimates show that income inequality is harmful for growth (see Alesina and Rodrik, 1994, Persson and Tabellini, 1994; Perotti, 1996), panel data models indicate that the relationship is not linear (e.g. Barro, 2000 and Banerjee and Duflo, 2003), positive (e.g. Forbes, 2000), or dependent on the time lag (e.g. Halter et al., 2014). Conversely, Castelló and Doménech (2002) and Castelló-Climent (2010) show that a more uneven distribution of human capital has a negative influence on the growth rates of per capita income in both cross-section and panel data models.

[16] In the first stages of development per capita income as well as income inequality increase, since there is a movement of population from the agricultural sector, characterized by a low per capita income and low inequality, to an industrial sector in which per capita income and income inequality are higher. Subsequently, when most of the population is in the industrial sector, per capita income increases and income inequality is reduced.

Table 5

Dependent Variable: $\ln Gini^y$

	OLS						FE					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\ln \frac{H}{L}$	-0.106^a	-0.109^a	-0.103^a	-0.042^a	-0.038^a	-0.021^c	-0.005	-0.022^c	-0.017	-0.026^b	-0.021^c	-0.001
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.017)
t		0.018^a	0.017^a	0.015^a	0.014^a			0.010^a	-0.003	-0.002	-0.005	
		(0.003)	(0.004)	(0.004)	(0.004)			(0.002)	(0.003)	(0.004)	(0.003)	
$\ln(\frac{X+M}{GDP})$			0.019	-0.029^b	-0.031^b	-0.065^a			0.038^a	0.023	0.023^c	0.048^b
			(0.015)	(0.013)	(0.013)	(0.019)			(0.013)	(0.014)	(0.014)	(0.021)
$ln\,(\frac{FA+FL}{GDP})$			-0.047^a	0.054^a	0.047^a	0.062^a			0.032^a	0.024^a	0.024^a	0.023^b
			(0.011)	(0.010)	(0.010)	(0.013)			(0.008)	(0.009)	(0.009)	(0.010)
lny				1.092^a	0.977^a	1.097^a				-0.234^b	-0.220^b	0.082
				(0.095)	(0.093)	(0.124)				(0.099)	(0.101)	(0.148)
$[lny]^2$				-0.068^a	-0.061^a	-0.069^a				0.016^a	0.015^b	-0.003
				(0.005)	(0.005)	(0.007)				(0.006)	(0.006)	(0.009)
$lnGini^h$				0.106^a		0.097^a				0.031		0.054^c
				(0.016)		(0.019)				(0.025)		(0.030)
$lnNo$					0.049^a						-0.001	
					(0.006)						(0.008)	
$lnGini^h_{Lit}$					0.018						-0.028	
					(0.022)						(0.024)	
$ln\frac{X^{high}}{X}$						0.015^b						0.007
						(0.007)						(0.005)
Constant	-1.423^a	-1.522^a	-1.527^a	-5.208^a	-4.949^a	-5.040^a	-1.009^a	-1.170^a	-1.158^a	-0.304	-0.382^a	-1.622^b
	(0.049)	(0.044)	(0.074)	(0.413)	(0.416)	(0.527)	(0.051)	(0.055)	(0.072)	(0.433)	(0.448)	(0.659)
R^2	0.131	0.122	0.164	0.444	0.456	0.467	0.110	0.032	0.050	0.068	0.068	0.151
Obs.	1040	1040	818	818	817	514	1040	1040	818	818	817	514
N	133	133	130	130	130	123	133	133	130	130	130	123
δ_i	*N*	*N*	*N*	*N*	*N*	*N*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
δ_t	*Y*	*N*	*N*	*N*	*N*	*Y*	*Y*	*N*	*N*	*N*	*N*	*Y*
Period	1960-2010	1960-2010	1970-2010	1970-2010	1970-2010	1985-2010	1960-2010	1960-2010	1970-2010	1970-2010	1970-2010	1985-2010

Notes: Robust standard errors in parenthesis. a, b and c are 1, 5, and 10 percent significance levels respectively.

ables bias, in column (4) we add the log of per capita income, the square of the log of per capita income, and the education Gini as additional explanatory variables. In line with the Kuznets curve, we find an inverted U-shape relationship between the level of development and income inequality.[17] More importantly, we also find a positive association between inequality in the distribution of education and in the distribution of income: the coefficient of the human capital Gini coefficient is positive and statistically significant at the 1 percent level. The components of human capital inequality, the share of illiterates, and the Gini among the literates are also related to higher income inequality, as shown in column (5). Nevertheless, although controlling for the level of development and the education Gini reduces the coefficient of the supply of skills by half, it continues being negative and statistically significant at the 1 percent level. We find, however, that the effect of globalization is highly dependent on the level of development. Once we control for non-linearities in per capita GDP, the coefficient of trade openness becomes negative, that of financial openness positive, and both are highly significant in all specifications. All results hold when the demand of skills is proxied with the share of high technology exports, as shown in column (6).[18]

As stated before, when we estimate equation (13) with fixed effects, which assumes $\delta_i \neq 0$, results are slightly different. The coefficients of the supply and demand of skilled workers have the expected sign in column (8) but are not statistically significant in several specifications. On the contrary, there is strong evidence pointing to globalization as a determinant of the recent increases in income inequality. The estimated coefficients of openness are positive and statistically significant, and do not change their sign when per capita income is included, suggesting that changes in the degree of trade and financial globalization have been highly related to changes in income inequality.

The results also differ for the Kuznets curve. When we use the variation of income inequality within countries, we do not find evidence in support of the Kuznets hypothesis. On the contrary, columns (10) and (11) show a U-shape relationship between per capita GDP and the income Gini, that is, as countries develop, there is a reduction followed by an increment in income inequality. This result reflects the upward trend in income inequality observed in many countries in the recent years. Nevertheless, the positive association be-

[17] Due to the scarcity of available income inequality data for long periods, it is difficult to test the Kuznets hypothesis empirically, and the evidence until now has been mixed. In a cross-section of countries, Ahluwalia (1976) found empirical support to the Kuznets hypothesis but Anand and Kabur (1993) showed that Ahluwalia's results were not robust to the use of alternative functional forms or different data sets. Using panel data, Deininger and Squire (1998) did not find an inverted U-shape relationship between the level of income and the Gini coefficient for the majority of countries in their sample (40 out of 49), whereas Barro (2000) finds some evidence in favour of the Kuznets curve.

[18] Data on high technology exports is available annually from 1988 onwards. In our sample, we use the data in 1988 as an observation in 1985.

tween education and income inequality holds in the fixed effect model; other things being equal, reductions in inequality in the distribution of education have been accompanied by reductions in the inequality in the distribution of income.

In general, the results of this subsection suggest an interesting explanation of the puzzle observed around the world, according to which changes in education inequality are not correlated with those in income inequality. Our results show that the fall in education inequality has reduced income inequality, but its effects have been offset by an increasing demand for skilled workers and the effect of globalization. In other words, the improvements in education and human capital inequality observed in many countries have not resulted in significant increases in income inequality due to forces in the opposite direction.

5. Conclusions

This paper has documented the trends in human capital inequality from 1950 to 2010 using an improved data set on human capital inequality. The evidence shows that most countries have experienced a very intense reduction in human capital inequality, mainly due to an unprecedented decrease in the share of illiterates, which has not been accompanied by a similar reduction in income inequality.

We do find that a plausible explanation for this puzzle could be that returns to schooling are increasing with the level of education. Thus, if returns to primary schooling are low, a large reduction in the share of illiterates may not translate to a sizeable increment in the wages of the population at the bottom end of the income distribution, when a smaller share of the population is also improving the human capital at the top. Using data for real GDP per worker for a broad number of countries, we estimate aggregate returns for different levels of education. Our results reveal that the returns to tertiary education are higher than those of secondary and primary schooling. These findings are also consistent with a low-quality educational system at the lower levels of schooling, which may lead to higher literacy but does not necessarily contribute to significant skill accumulation (e.g., Hanushek and Woessmann, 2012).

A complementary explanation is that improvements in literacy and wages of the population at the bottom end of income distribution have also coincided with increased wages in other cohorts of population with higher education, such that all of them maintain their income shares. The latter could reflect exogenous factors such as globalization or skill-biased technological progress, which have increased wages at the top. Under these conditions, improvements in education and human capital inequality observed in many countries have avoided significant increases in income inequality. Our results find empirical support for this hypothesis and indicate that the positive effect of the reduction in the

Gini coefficient of education on income inequality has been offset by the increase in the demand of skilled workers and the effect of globalization.

The evidence presented in this paper is highly relevant for development policies. Many governments have made a great effort towards eradicating illiteracy rates, but these policies have not been accompanied by a more even distribution of income, due to the presence of other offsetting forces. This evidence does not imply that educational policies have not reduced poverty and improved wages and the standards of living of hundreds of millions with better education. On the contrary, the eradication of illiteracy is a necessary condition to ensure access to higher levels of education for all people, and better education is crucial to increase average earnings per worker and to avoid the effects of skill-biased technological progress and globalization on greater income inequality.

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Appendix

We have checked whether improvements in the income going to the first quintile have also been accompanied by improvements in the share of income going to the top quintile, so that both changes have made the income Gini coefficient to remain largely unchanged over time. The problem to test this hypothesis is that the most reliable data on the different parts of the income distribution, comparable across countries, is that of the LIS data set. However, as stated above, it includes data for a few wealthy economies and the greatest reductions in the share of illiterates have taken place in the developing countries. As an alternative, we have used data on the distribution of income by deciles from the UNU-WIDER World Income Inequality Database (WIID), which consists of an update of the Deininger & Squire database from the World Bank, new estimates from the Luxembourg Income Study and Transmonee, and other new sources. The version we have used is UNU-WIDER World Income Inequality Database, Version 2.0c, May 2008. Given there are very few observations to create a balanced panel, under the criteria of using only high quality data and the same original source, we have taken the first and the last available observation of income deciles in each country and we have computed the difference in several income quintiles. Then, for each country, we have computed the absolute changes in income for the same time period for which the income deciles are available.

Figure A.1 plots the increment within a country in the share of income going to the first and fifth quintiles. The figure indicates that there is no systemic positive relation between both variables. In contrast, the correlation is clearly negative. Furthermore, we find a weak evidence suggesting that a reduction in the share of illiterates has resulted in an increase in the share of income going to the poorest 20 percent of the population. Figure A.2 displays the change in the share of illiterates for the population 15 years and above and the change in the first quintile in the distribution of income. As we can observe, there is not a marked negative relationship among both variables. In countries such as Mexico, Spain, Brasil or Indonisia there has been a significant reduction in the share of illiterates but the income accruing to the bottom quintile has remained almost constant.[19]

[19] This sample of countries does not show either a clear positive relationship between the increment in the share of illiterates and the increment in the income going to the poorest 60 percent of the population (cummulative third quintile). At the other extreme, we do not find either that an increment in the share of education going to the top education quintile is related to an increase in the share of income going to the top income quintile. In fact, the correlation between the increment in the income and in the education of the respective top quintiles is almost zero.

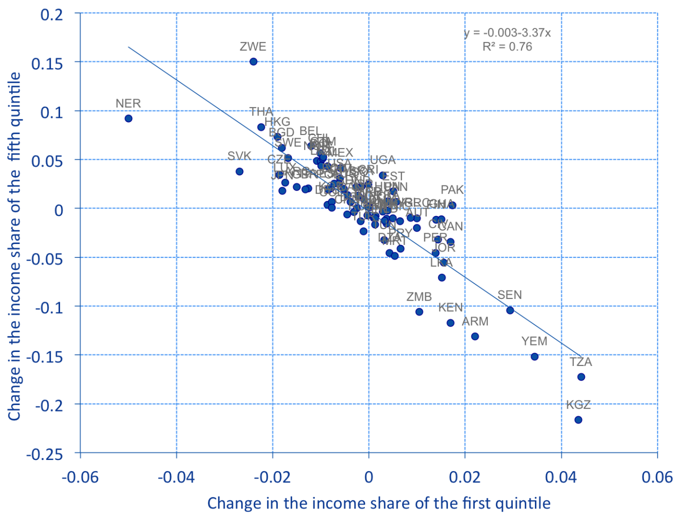

Figure 12: ***Figure A.1***: *Change in the income shares of the first and fifth quintiles.*

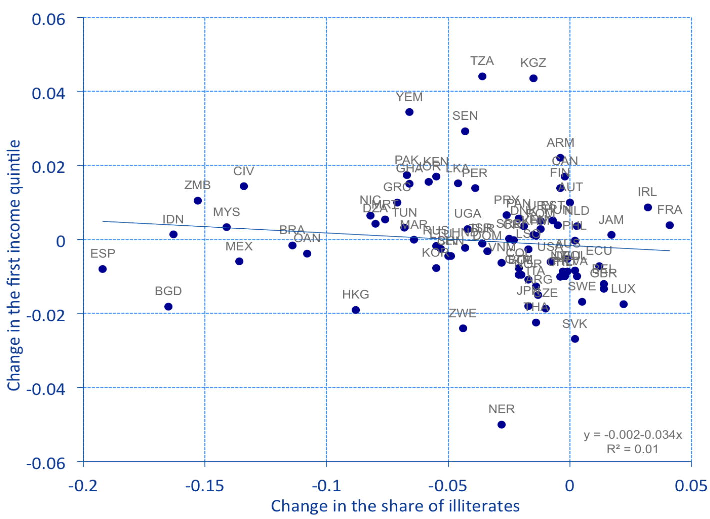

Figure 13: ***Figure A.2:*** *Changes in the shares of illiterates and the first income quintile.*

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