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Amparo Castelló-Climent /
R. Doménech

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Amparo Castelló-Climent[a] and Rafael Doménech[a,b]

a University of Valencia, Spain
b BBVA Research, Spain

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Abstract

This paper explores the relationship between human capital inequality and income inequality, using an updated data set on human capital inequality for 146 countries from 1950 to 2010 and a novel database on earnings inequality. We find an inverted U-shaped relationship between these two inequality indicators, but with significant differences across countries regarding the turning point where the relationship between human capital inequality and earnings inequality becomes positive. Along with the development process in dual economies, we find that skill-biased technological change is an additional force that may blur the relationship between human capital and earnings inequality. We also find that the effect of earnings inequality on income inequality is statistically significant, relatively stable and economically relevant. Approximately each one-point change in the Gini coefficient of earnings contributes on average to a half-point change in the Gini coefficient for income. Finally, the paper shows that, over and above the effect exerted through earnings inequality, human capital inequality has a direct positive effect on income inequality.

Keywords: education inequality, wage inequality, income inequality.
JEL Classification: I24, O11, O15, O5.

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1. Introduction

In the last few decades, most developing countries have made major efforts to eradicate illiteracy, reducing the number of illiterates by several hundreds of millions. As a result, the inequality in the distribution of education in the world has halved: the average Gini coefficient for human capital inequality dropped from 0.55 in 1960 to 0.28 in 2005. Conversely, the evolution of income inequality has remained quite stable over the long run. The value of the average income Gini coefficient was almost the same in 2005 (0.41) as it had been in 1960 (0.42). This divergent path could indicate that human capital and income inequality are uncorrelated. Conversely, the reduction in human capital inequality could have been offset by other forces that have driven income inequality upwards. The aim of this paper is to explore whether there is a relationship between human capital inequality and income inequality or if, on the contrary, the two distributions are uncorrelated.

So far, the literature has not provided a clear answer to the question. As a theoretical foundation for the empirical exercise, most of the studies compute the variance of a standard earning function that relates earnings with the average years of schooling and its return. However, the majority of the empirical evidence is from data on income inequality instead of earning inequality. As long as capital income represents a relatively small fraction of total income, earnings inequality and income inequality should be highly correlated. However, some studies suggest labor shares have declined in several countries since the early 1980s (Karabarbounis and Neiman, 2013), and others show an increase in wealth-to-income ratios since the 1970s (Piketty and Zucman, 2014).

The lack of consensus in the literature analyzing the relationship between education inequality and income inequality could be explained by the use of different measures of inequality, samples and econometric techniques. Chiswick (1971) finds a positive relationship between earnings inequality, measured through different percentiles, and inequality of schooling, measured through the Lorenz curve, in a small sample of nine countries. In line with this finding, but using a measure of income instead of earnings, Winegarden (1979) finds an inverse relationship between the variance in schooling and income equality in a sample of 32 countries. These results were questioned by Ram (1984), who finds no evidence that the variance of years of schooling is negatively related to several measures of income equality in a sample that includes 28 countries, of which 26 were classified as 'developing'. More recent contributions that include samples with a large number of countries and periods also report contradictory findings. De Gregorio and Lee (2002) find that a more equal distribution of education, as measured with the standard deviation of educational attainment, is related to a more equal distribution of income. Using fixed-effects estimates, Földvári and van Leeuwen (2011) do not find a positive relationship between education inequality and the income Gini coefficients, whereas Lee and Lee (2018) show the Gini coefficient of educational attainment has a significant and positive effect on income inequality.

In this paper we provide a comprehensive analysis of the relationships among the levels of inequality in human capital, earnings and income in a broad section of countries. We estimate models that use the cross-sectional variation in the data, as inequality variables are quite persistent over time, and check the robustness of the results in specifications that control for time-invariant characteristics. Since the relationship between human capital and income inequalities may depend on the level of development, we also check whether the relationships differ in less developed and in advanced economies.

We first compile a comprehensive data set on human capital inequality variables, covering 146 countries from 1950 to 2010, extending the previous data set produced by Castelló and Doménech (2002). In this new version, we use the educational attainment data set provided by Barro and Lee (2013), which includes more countries and years, reduces some measurement errors, and solves some of the shortcomings pointed out by De la Fuente and Doménech (2006 and 2015) and Cohen and Soto (2007). We also compute a more precise human capital Gini coefficient using seven levels of schooling, and distinguishing between those individuals that have completed a given level of education and those that have not.

Secondly, in contrast to most studies that use data on income inequality instead of earnings inequality to analyze the effects of human capital inequality, in this paper we use a novel data set on earnings inequality computed by Hammar and Waldenström (2020). The data includes information on earnings, taxes, working hours, and local prices for workers in the main representative occupations in 68 countries. An additional advantage of this data set is that variables are comparable across countries and periods, since data have been collected in the same way every third year since 1970.

We then analyze the relationship between human capital inequality and earnings inequality, and we find an inverted U-shape between the two inequality indicators. On average, the Gini coefficient for labor earnings inequality reaches its maximum when the share of illiterates is about 40 percent. Nevertheless, we show significant differences across countries regarding the turning point where the relationship between human capital inequality and earnings inequality becomes positive.[1] The literature has explained the inverted U-shaped relationship as a composition effect resulting from the fall in the share of the population with no schooling in dual developing economies (e.g., Robinson, 1976,

[1] Lim and Tang (2008) and Morrison and Murtin (2013) use the Mincer specification of human capital to develop a separate measure of human capital inequality from that of education inequality. When they plot the relationship between human capital and human capital inequality, they find that, as average human capital increases, human capital inequality first increases and then decreases. They thus name it the "Human Capital Kuznets Curve". Unlike these studies, and in line with our previous papers, we refer to education inequality as human capital inequality.

Knight and Sabot, 1983, and Anand and Kanbur, 1993). We test this explanation formally and find a non-linearity between the Gini of earnings and the share of illiterates that holds even after controlling for the level of income and its square, and is robust in specifications that control for country-specific effects.

Thirdly, we analyze an additional force to the development process in dual economies that may blur the relationship between human capital and earnings inequality, as it is skill-biased technological change (SBTC). Thus, the reduction in the share of illiterates over the years and, consequently, in the human capital Gini coefficient has coincided with a process of technological change that has mainly benefited the skilled workers (e.g., Katz and Murphy, 1992). Despite the increase in the relative supply of skilled workers, the growing wage gap between wages at the top and at the bottom of the wage distribution could have partially offset the improvements in the distribution of human capital. We test the SBTC hypothesis in our relatively large sample of countries. We find evidence confirming that, despite the increase in the relative supply of skilled workers, labor earning inequality has increased over the years due to SBTC. We find that earning inequality has increased by an average of 0.62 percent each year in our sample period.

Fourthly, after analyzing the effects of human capital inequality on earnings inequality, we then estimate the average contribution of earnings inequality to income inequality. Our findings indicate that this contribution is statistically significant, relatively stable and economically relevant. Our results also suggest that approximately each one-point change in the Gini coefficient of earnings contributes to a half-point change in the Gini coefficient of income.

Finally, to complete the analysis, we show that in addition to its effects through earnings inequality, human capital inequality also influences income inequality directly. In a regression where the income Gini coefficient is the dependent variable, our results indicate that even after controlling for earnings inequality, the coefficient of the human capital Gini index is positive and statistically significant. A large part of the direct effect of human capital inequality on income inequality is found to be driven by channels related to redistribution, fertility, trade openness and financial globalization. Our results hold in a fixed-effects model that controls for country-specific characteristics and exploits the within-country variation in the data.

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 and compares it with that of human capital inequality. Section 4 analyzes the relationship between human capital inequality and income inequality through its effect on earnings inequality. Section 5 estimates the contribution of human capital inequality to income inequality through indirect channels. Finally, section 6 presents the main conclusions.

2. Evolution of human capital inequality over time

Castelló and Doménech (2002) were the first to provide a comprehensive data set on human capital inequality, taking the educational attainment levels from Barro and Lee (2001) and calculating the Gini coefficient and the distribution of education by quintiles for a large number of countries and periods. However, some studies have demonstrated a number of problems with the Barro and Lee (2001) data set: for example, Cohen and Soto (2007) and de la Fuente and Doménech (2006) reveal that the data show implausible time series profiles for some countries. Barro and Lee (2013) addressed most of these concerns in an improved data set that reduces measurement error and improves 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. The old and the new measures of the average years of schooling are highly correlated in levels but there is little relationship when the variables are measured in differences. This suggests lower measurement error in the new indicators due to a smoother trend in the attainment levels. Using the new Barro and Lee (2013) data set, we have updated and expanded the inequality indicators to cover 146 countries for five-year time spans between 1950 and 2010, thereby obtaining 1898 observations.

To compute the human capital Gini coefficient, we have extended the methodology of Castelló and Doménech (2002) to include a broader set of educational levels that distinguish between completed and incomplete levels. This is particularly relevant in less developed economies with high student dropout rates. Our Gini coefficient is now calculated as follows:

$$Gini^h = \frac{1}{2\overline{H}} \sum_{i=0}^{6} \sum_{j=0}^{6} \left| \widehat{x}_i - \widehat{x}_j \right| n_i n_j \tag{1}$$

where $\overline{H}$ is the average years of schooling in the population aged 15 and over, 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 is the share of the population with a given level of education: no schooling (0), incomplete primary (1), completed primary (2), lower secondary (3), upper secondary (4), incomplete tertiary (5), and completed tertiary education (6).[2]

[2] x_i is the duration in years of schooling of each educational level, and the cumulative average years of schooling are computed as: $\widehat{x}_0 \equiv x_0 = 0$, $\widehat{x}_1 \equiv x_1$, $\widehat{x}_2 \equiv x_1 + x_2$, $\widehat{x}_3 \equiv x_1 + x_2 + x_3$, $\widehat{x}_4 \equiv x_1 + x_2 + x_3 + x_4$, $\widehat{x}_5 \equiv x_1 + x_2 + x_3 + x_4 + x_5$, $\widehat{x}_6 \equiv x_1 + x_2 + x_3 + x_4 + x_5 + x_6$. Appendix A1 describes the procedure followed to compute duration in years of schooling of each educational level from Barro and Lee's (2013) data set, and shows how the additional information provided by the larger number of educational levels increases the precision of

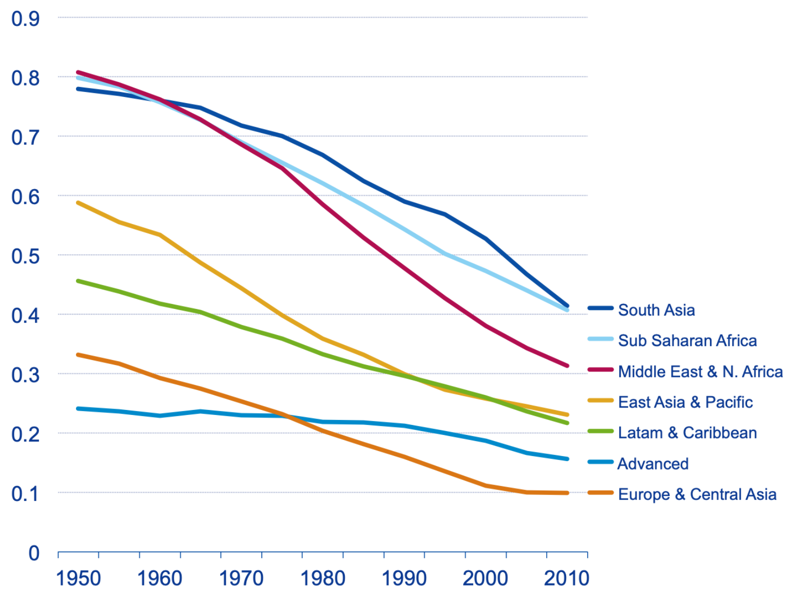

Figure 1: *Human Capital Gini Coefficient of population aged 15+.*

In spite of the large differences in the distribution of education across regions, there has been a general reduction in human capital inequality worldwide, as clearly shown in Figure 1. In most regions, the decline has been remarkable, with the Gini coefficients reduced by more than half. As shown in Appendix 2, the overall increase in the share of education going to the third quintile and the increase in the ratio of the bottom to the top quintile suggests the improvement in equality has mainly benefited the lowest part of the distribution.[3]

Further examination of the data reveals that the large reduction in education inequality is mainly due to a sizable decline in illiteracy. Without exception, all the countries that have experienced a substantial reduction in the share of illiterates also show a similar decline in the human capital Gini coefficient over time, suggesting the reduction in the Gini coefficient over time has been largely determined by the decline in the share of illiterates, as pointed out by Morrison and Murtin (2013). This fact can be explained by the weight of the share of illiterates in the computation of the human capital Gini coefficient.

the new Gini coefficient.

[3] We compute the ratio of 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 therefore the value of the bottom quintile in that case is equal to zero.

To illustrate this point, we reorganize equation (1) as follows:

$$Gini^h = n_0 + \frac{A}{\overline{H}} \tag{2}$$

where:

$$A = \sum_{i=1}^{6}\sum_{j=1}^{6} \left|\widehat{x}_i - \widehat{x}_j\right| n_i n_j$$

The Gini coefficient of education is, therefore, a proportional measure of the share of illiterates. A notable reduction in this share translates into a similar reduction in the Gini coefficient. Whether the reduction in the Gini coefficient is greater or smaller than that in the share of illiterates will depend on the changes in the distribution of education among the literates. Given that:

$$Gini^{LIT} = \frac{1}{2\overline{H}^{LIT}} \sum_{i=1}^{6}\sum_{j=1}^{6} \left|\widehat{x}_i - \widehat{x}_j\right| n_i^{LIT} n_j^{LIT} \tag{3}$$

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 the population with no education, equation (3) can be rewritten as follows:

$$Gini^{LIT} = \frac{1}{(1-n_0)} \frac{A}{\overline{H}} \tag{4}$$

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

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

When the share of illiterates is very high, the evolution of the human capital Gini coefficient is mainly determined by the share of illiterates, as in the case of less developed countries. On the other hand, in advanced economies, where the share of illiterates is almost zero, the distribution of primary, secondary and tertiary education is what determines the evolution of education inequality.

We can use the previous expression to analyze the contribution of the share of illiterates to the changes in $Gini^h$ from 1950 to 2010:

$$Gini^h_{2010} - Gini^h_{1950} = (n_{0,2010} - n_{0,1950}) + (1 - n_{0,n_{0,2010}}) Gini^{LIT}_{2010} - (1 - n_{0,n_{0,1950}}) Gini^{LIT}_{1950}$$

In our sample of 146 countries, the average reduction in $Gini^h$ is 0.3 (from 0.557 in 1950 to 0.257 in 2010), whereas the average reduction in the share of illiterates is 0.34. Therefore, the change in n_0 explains on average 114 percent of the change in $Gini^h$.

3. Evolution of Income Inequality

To analyze the relationship between income and human capital inequality, we start by comparing the mean values of the human capital and income Gini coefficients for those countries with available data on income inequality. We measure income inequality through the disposable income Gini coefficient taken from the Standardized World Income Inequality Database (SWIID), version SWIID v8.1, which uses a custom missing-data algorithm to standardize WIID from the Luxembourg Income Study (LIS) data set.[4] The data cover 96 countries with observations from 1985 to 2010.[5]

If we compare the average values 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 those with the highest and the lowest inequality in the distribution of education do not coincide.[6] The most remarkable example is that of Latin America and the Caribbean, which is one of the regions with the highest income inequality but only moderate inequality in the human capital distribution. At the other extreme, countries in South Asia display high inequality in the distribution of education but relatively low inequality in the distribution of income.

Education and income inequality have also evolved differently over recent decades. The data indicate that the income Gini coefficient, on average, has remained quite stable over the long run. For the whole sample, the income Gini coefficient was 0.361 in 1985 and 0.377 in 2010. This evidence is illustrated in Figure 2, which plots the evolution of the income Gini coefficient for all the regions and available time periods. In some regions, the income Gini coefficient has slightly increased over the years, whereas in Latin America and the Caribbean, and in the Middle East and North African regions, it has decreased.

[4] 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, there are concerns about the poor quality of income inequality data covering multiple countries due to problems of cross-country comparability and the incompleteness of coverage across countries and over time (e.g., Atkinson and Brandolini, 2001). The most reliable data set on income inequality is the Luxembourg Income Study (LIS), which 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, mostly starting in 1980, which reduces the sample size considerably.

[5] The income inequality data in version 8.1 is of higher quality than in previous versions (SWIID v3.0). However, the data set contains fewer observations in the initial years. For instance, the 8.1 version contains only 14 observations in 1960, 41 observations in 1970, and 63 observations in 1980. In order to include a greater number of countries in the sample, we have chosen 1985 as our starting period.

[6] Appendix A.2 shows the mean values of the income and human capital Gini coefficients for several regions of the world.

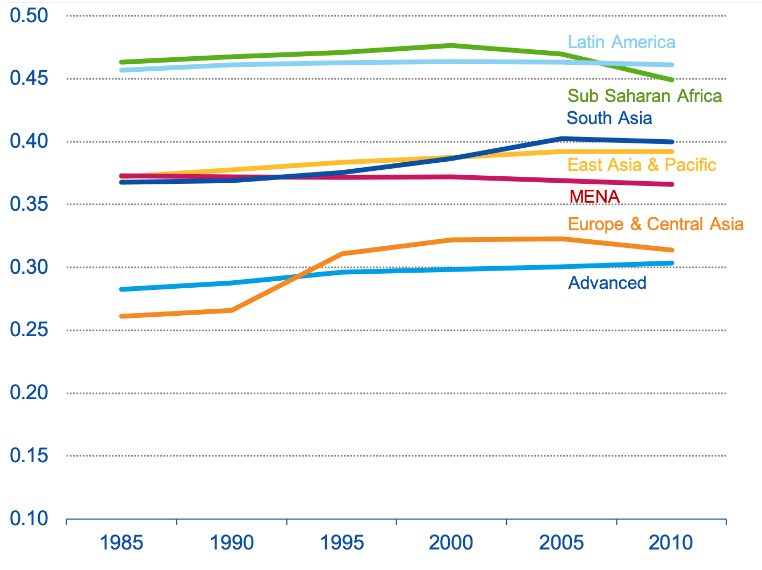

Figure 2: *Evolution of the income Gini coefficient across regions*

In the following sections we explore whether human capital inequality has any effect on income inequality or if, on the contrary, the two distributions are totally uncorrelated.[7] Before explaining in more detail the effects of human capital inequality on income inequality, it should be taken into account that there are other sources of income apart from wages, such as those coming from capital ownership and entrepreneurship, or from net transfers and taxes, which also influence income inequality.

Changes in the income Gini coefficient are also affected by composition effects resulting from changes in the distribution of labor and capital income. Karabarbounis and Neiman (2013) report evidence of a decline in the labor share in a large majority of countries and industries since 1975. At the same time, although the evidence is very scarce due to the lack of data on asset distribution for a broad set of countries, Piketty and Zucman (2014) have documented an increase in wealth-to-income ratios since the 1970s in the top

[7] Previous contributions to the literature have found that income inequality is positively correlated with education inequality and negatively related to education (e.g., Becker and Chiswick, 1966, Ahluwalia, 1976, or Park, 1996). Others, however, found that schooling inequality has a marginal negative, rather than positive, effect on income inequality (Ram, 1984). Sylwester's (2002) findings suggest that government expenditures for public education are associated with falling income inequality. 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. In a comprehensive analysis of the determinants of inequality, Roser and Cuaresma (2016) show the evolution of income inequality in 32 developed countries has been explained by international trade, the government size, the interaction of technology and education, and political and institutional factors.

eight developed economies. In other countries for which we have only recent data and no evidence about the changes over time, the distribution of wealth is more unequal than the distribution of income. Additionally, Checchi and García-Peñalosa (2010) show that the labor share is negatively correlated with the income Gini coefficient. In what follows, we focus on how changes in the distribution of human capital have affected the distribution of the labor income component, and whether there is any direct effect of human capital inequality on income inequality over and above wage inequality.

4. Human capital inequality, earnings inequality and income inequality

4.1 Human capital inequality and earnings inequality

To analyze the correlation between human capital and labor income inequality, we use a new global inequality data set on labor earnings in the working population for 68 developed and developing countries from 1970 to 2018 assembled by Hammar and Waldenström (2020). These authors show that changes in the labor income inequality trend have been mainly driven by real wage growth, rather than hours worked, taxes or changes in employment by occupations.

In this sample of countries and years we find an inverted U-shaped relationship between the human capital and the labor income Gini coefficients.[8] On average, the Gini coefficient of labor income reaches its maximum when the share of illiterates is around 40 percent, which corresponds to an average of 5.5 years of schooling. However, the nonlinear relationship between the share of the population with no schooling and the Gini of labor income found for the whole sample hides the fact that this relationship is, as expected, not uniform across countries.

To illustrate this point, in Figure 3 we have selected five countries to show that, although they provide a good approximation of the result for the whole sample, there are significant differences across them regarding the turning point where the relationship between population with no schooling and labor income inequality changes from positive to negative. Thus, the average estimated turning point (when $n_0 = 0.37$) is a good approximation for a country like India. Conversely, for other countries such as Pakistan (0.45), Kenya (0.27), Colombia (0.12) or France (0.05), the turning points occur at different values

[8] Previous contributions to the literature have simulated a monetary equivalent of years of schooling in a Mincerian wage equation. Lim and Tang (2008) estimate a Mincerian measure of human capital income from 1960 to 2000 and find an inverted U-shape assuming the same world average rates of return that decrease with the level of education. Morrison and Murtin (2013) also report a human capital Kuznets curve over the course of educational development for 32 'macro-countries' over the period 1870-2010, imposing homogeneity of returns across countries.

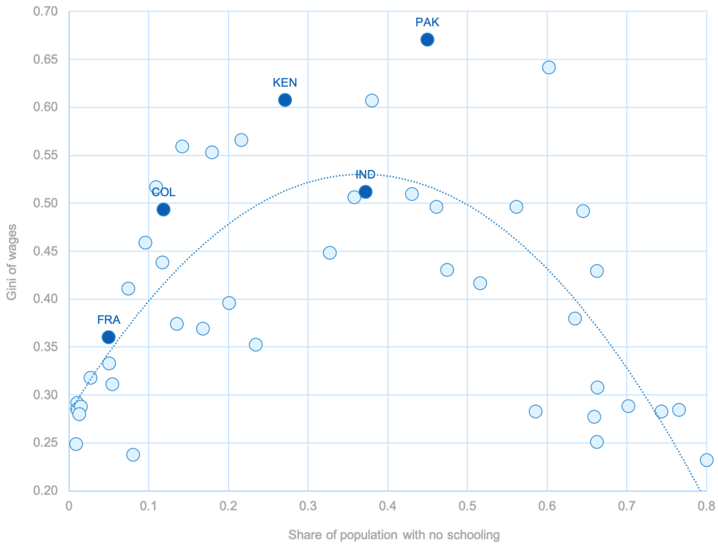

Figure 3: *Share of the population with no schooling and Gini coefficient of labor income in several countries, 1970-2010.*

of the share of the population with no schooling.

The main explanation for the non-linearity is the composition effect of the share of the population with no schooling. Several papers have shown that in an economy with two population groups—low and high educational level—a transfer of workers from the former to the latter raises the inequality of wages to the point where the high-education group reaches a certain share (see Robinson, 1976; Knight, 1976; Knight and Sabot, 1983; Anand and Kanbur, 1993; Fields, 1993). Note that, while the share of the population with no education is still large, the increase in wage inequality as a result of the transfer of workers from the low- to the high-education group is, according to Fields (1979), a statistical artifact and not an economically meaningful worsening of the income distribution. On the contrary, this is a transitory effect of an economic development process that is good in absolute income terms and that reverts when n_0 falls sufficiently and more people are educated, at least to the level of completed primary schooling. Eradicating illiteracy and completing primary schooling are, therefore, necessary conditions for the subsequent improvement of per capita income and equality, showing that there is no trade-off between them. They are not sufficient conditions because, as discussed before, other factors such as the increase in the capital income share, wealth inequality or a less redistributive fiscal system may more than offset the fall in wage inequality.

Table 1.a provides a formal analysis of the relationship between the Gini coefficients of human capital (Gini^h) and labor income ($Gini(W^E)$) in a sample of 68 countries from

1970 to 2010. Column (1) displays a strong correlation between the two variables. The results indicate the relationship is not linear: the estimate of Gini^h is positive but the square term is negative, and both are statistically significant at the 1 percent level. As stated above, the explanation given for the non-linearity is the composition effect from the reduction in the share of illiterates. We test this explanation and decompose the human capital Gini coefficient into two components: the part explained by the share of illiterates, and the part explained by inequality among the literates (see equation (2)). Column (2) shows that the estimated coefficient of the share of illiterates is positive, its squared term is negative, and both are statistically significant at the 1 percent level. This finding suggests the composition effect is an important explanation for the non-linearity observed between the Gini coefficient of human capital and the Gini coefficient of earnings. However, the composition effect of the share of illiterates is not the only explanation since human capital inequality among literates is also statistically significant. Thus, column (2) also shows a slightly convex relationship between the Gini of labor income and the component of human capital inequality that reflects inequality among the literate population. Columns (3) and (4) control for per capita income ($ln\ y$) and its square, to take into account the level of development. Results show the non-linearity with regard to the human capital Gini coefficient and its two components still holds even when we include the level of income per capita and its square.

In order to analyze the results in more detail, we have split the sample into less developed (41 countries) and developed economies (23 countries). Columns (5) to (12) show the results for the same specifications in columns (1) to (4). In general, the main results for the whole sample still hold in the sample of less developed economies, as is the case with the inverted U-shaped relationship between the human capital and the labor income Gini coefficients, or the relevance and significance of the share of illiterates. In the case of advanced economies, however, the statistical significance of many coefficients vanishes, suggesting that the results obtained in the whole sample are mainly driven by less developed economies. In the sample of advanced economies the coefficient of $Gini^h$ is positive and statistically significant, but its squared term is not significant, although it is still negative. This is not surprising since only 3 observations for Turkey, out of 207 in the sample of advanced economies, present a $Gini^h$ greater than the turning point of the U-shaped inverted relationship between human and labor Gini coefficients.

Table 1.a

Dependent Variable: $Gini(W^E)$

	OLS											
	Whole Sample				Less Developed				Advanced			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Gini^h$	1.017^a		0.837^a		0.968^a		0.950^a		0.464^b		0.454^b	
	(0.090)		(0.099)		(0.097)		(0.100)		(0.196)		(0.212)	
$Gini^{h^2}$	-0.897^a		-0.820^a		-0.972^a		-0.953^a		-0.269		-0.445	
	(0.104)		(0.131)		(0.108)		(0.127)		(0.316)		(0.379)	
No		1.183^a		1.112^a		1.331^a		1.535^a		-0.039		0.512
		(0.211)		(0.223)		(0.228)		(0.260)		(0.612)		(0.581)
(A/H)		-0.879^b		-0.770^b		-0.054		-1.304^c		-0.331		-0.764^b
		(0.427)		(0.363)		(0.621)		(0.709)		(0.362)		(0.359)
No^2		-1.399^a		-1.319^a		-1.320^a		-1.624^a		-0.563		-1.231^b
		(0.228)		(0.239)		(0.256)		(0.279)		(0.561)		(0.560)
$(A/H)^2$		2.995^a		2.731^a		2.375		5.623a		1.025		2.062^b
		(1.038)		(0.873)		(1.607)		(1.864)		(0.837)		(0.815)
$2 * No * (A/H)$		-0.665^b		-0.957^b		-1.818^a		-2.071^a		1.634		0.201
		(0.391)		(0.406)		(0.425)		(0.503)		(1.260)		(1.224)
lny			0.198^b	0.233^a			0.132	0.177^c			0.097	-0.059
			(0.086)	(0.085)			(0.096)	(0.096)			(0.312)	(0.297)
lny^2			-0.014^a	-0.016^a			-0.009^c	-0.012^b			-0.008	-0.001
			(0.005)	(0.005)			(0.005)	(0.005)			(0.016)	(0.015)
Constant	0.037a	0.230^a	-0.559	-0.568^c	0.181^a	0.165^a	-0.299^b	-0.317	0.143^a	0.234^a	-0.023	0.888
	(0.021)	(0.043)	(0.391)	(0.395)	(0.020)	(0.057)	(0.438)	(0.434)	(0.027)	(0.037)	(1.539)	(1.473)
R^2	0.230	0.267	0.460	0.482	0.188	0.213	0.264	0.293	0.260	0.325	0.330	0.390
Obs.	576	576	529	529	369	369	322	322	207	207	207	207
Countries	64	64	64	64	41	41	41	41	23	23	23	23
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Ordinary Least Squares estimation. Robust Standard errors in parentheses. a, b, and c are 1, 5, and 10 percent significance levels, respectively. The dependent variable is the Gini coefficient of yearly earnings.

Table 1.b

Dependent Variable: $Gini(W^E)$

	FIXED EFFECTS											
	Whole Sample				*Less Developed*				*Advanced*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Gini^h$	0.709^a		0.739^a		0.768^a		0.795^a		0.453^b		0.453^c	
	(0.118)		(0.138)		(0.164)		(0.198)		(0.224)		(0.232)	
$Gini^{h^2}$	-0.949^a		-0.949^a		-1.008^a		-1.058^a		-0.803^a		-0.751^b	
	(0.108)		(0.131)		(0.136)		(0.172)		(0.271)		(0.320)	
No		0.792^a		0.753^a		0.863^a		0.970^a		1.125^b		0.865
		(0.208)		(0.239)		(0.253)		(0.314)		(0.549)		(0.529)
(A/H)		-0.084		-0.284		-0.197		-0.700		-0.422		-0.515
		(0.385)		(0.450)		(0.562)		(0.758)		(0.482)		(0.458)
No^2		-1.150^a		-1.124^a		-1.220^a		-1.363^a		-1.838^a		-1.517^a
		(0.188)		(0.212)		(0.225)		(0.274)		(0.559)		(0.559)
$(A/H)^2$		0.502		0.730		0.926		2.136		0.922		1.162
		(0.845)		(1.000)		(1.273)		(1.915)		(0.997)		(0.943)
$2 * No * (A/H)$		-0.926^b		-0.762^c		-1.043^b		-1.227^b		-1.612		-1.069
		(0.380)		(0.432)		(0.449)		(0.553)		(1.047)		(1.020)
lny			0.165^a	0.184^a			0.186^b	0.207^a			0.148	0.218
			(0.059)	(0.058)			(0.077)	(0.077)			(0.031)	(0.336)
lny^2			-0.008^b	-0.009^a			-0.009^c	-0.009^b			-0.013	-0.017
			(0.003)	(0.003)			(0.004)	(0.004)			(0.016)	(0.016)
Constant	-0.279a	-0.379^a	-0.529^c	-0.483^c	0.314^a	0.428^a	-0.756^b	-0.702^b	0.169^a	0.255^a	0.086	-0.190
	(0.061)	(0.073)	(0.272)	(0.274)	(0.077)	(0.095)	(0.334)	(0.339)	(0.035)	(0.056)	(1.688)	(1.721)
R^2	0.238	0.250	0.244	0.264	0.266	0.277	0.292	0.309	0.206	0.247	0.303	0.340
Obs.	576	576	529	529	369	369	322	322	207	207	207	207
Countries	64	64	64	64	41	41	41	41	23	23	23	23
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Fixed-effects estimation. Standard errors in parentheses. a, b, and c are 1, 5, and 10 percent significance levels, respectively. The dependent variable is the Gini coefficient of yearly earnings.

In Table 1.b we present the results for the same specifications and samples as before, but now including country fixed effects. As we can see in Table 1, the main results are robust to the estimation method. In particular, the non-linearity of $Gini^h$ and the inverted U-shaped relationship between the human capital and the labor income Gini coefficients, the significance of the share of illiterates, and the robustness of the results to the inclusion of income per capita still hold when fixed effects are taken into account. In this case, the inverted U-shaped relationship between $Gini^h$ and $Gini(W^E)$ is also statistically significant, suggesting that fixed effects are relevant to control for heterogeneity across countries.

4.2 Skill-biased technological change

Despite the increase in the supply of educated workers, the demand for skills may have kept pace with the human capital investment, leaving earnings dispersion unchanged. For example, it could be the case that an individual (or quintile) with no education in t becomes educated in $t+1$, but the increase in their income occurs at the same time as the increase achieved by individuals with higher educational attainment, who benefit from the increase in wages due to skill-biased technological change (SBTC). As a result, although there is a reduction in schooling inequality, income inequality remains unchanged.

The "canonical model" 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 SBTC. The motivation behind this literature is the observation that in the United States and other developed countries, in spite of the growing 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 for skills, driven by SBTC, and the increase in the supply of skills. When the relative demand increases faster than the relative supply, wage dispersion rises. Conversely, when the supply outpaces the demand, wage dispersion decreases.

We test the canonical model of the race between education and technological change. Following the seminal work of Katz and Murphy (1992), we relate the earning gap or skill premium (i.e., the wage ratio of skilled to 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

Table 2
Dependent variable: Gini(W^E) Yearly Earnings

	OLS			FE		
	Whole	Less Dev.	Advanced	Whole	Less Dev.	Advanced
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln \frac{H}{L}$	-0.099^a	-0.061^a	-0.069^a	-0.053^a	-0.059^a	-0.044^c
	(0.011)	(0.015)	(0.014)	(0.014)	(0.019)	(0.023)
t	0.031^a	0.019^a	0.023^a	0.016^a	0.017^a	0.015
	(0.006)	(0.007)	(0.008)	(0.005)	(0.006)	(0.009)
Constant	-1.586^a	-1.297	-1.734^a	-1.408^a	-1.281^a	-1.638^a
	(0.070)	(0.077)	(0.087)	(0.060)	(0.078)	(0.097)
R^2	0.099	0.050	0.093	0.026	0.030	0.020
Obs.	576	369	207	576	369	207
Countries	64	41	23	64	41	23
δ_t	N	N	N	N	N	N

Notes: Robust standard errors in parentheses. a, b and c are 1, 5, and 10 percent significance levels respectively. Dependent variable is the Gini coefficient of yearly earnings

(t):[9]

$$\ln(\frac{w_{H_t}}{w_{L_t}}) = \frac{\sigma-1}{\sigma}\gamma_0 + \frac{\sigma-1}{\sigma}\gamma_1 t - \frac{1}{\sigma}\ln(\frac{H_t}{L_t}) \tag{6}$$

where σ is the elasticity of substitution between high-skilled and low-skilled labor, H refers to the share of the population aged 25 and over with tertiary education, and L is the share of the population aged 25 and over with primary schooling.[10]

The results displayed in Table 2 suggest that SBTC could have offset the effect of the fall in human capital inequality over time. Column (1) shows the relative supply H/L enters with the correct sign; a higher relative share of the population with tertiary education is related to less earnings inequality. The elasticity of substitution between the population with tertiary education and those with primary schooling is about 10.1 ($\sigma = 1/0.099$). On the demand side, the coefficient of the time trend is positive, statistically significant and equal to 0.031, that is, earning inequality has increased by an average of 0.62 percent each year. The results hold in the less developed countries, in the advanced economies, and in the specification that controls for country fixed effects.

[9] In the literature it is commonly assumed that there is a log-linear increase in the demand for skills over time coming from technology, captured as follows:

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

[10] We proxy the earning gap or skill premium, that is, the wage ratio of skilled to unskilled workers, with the Gini coefficient of earnings.

4.3 Earnings inequality and income inequality

We complete the analysis of the relationship between years of schooling and income inequality with an estimation of the contribution of earnings inequality to total income inequality.[11]

The literature on inequality provides different methods to compute the contribution of a particular component of income, factor or subgroup of population to income inequality (see, for example, the review by Cowell and Fiorio, 2011). Here we use the method proposed by Fei, Ranis, and Kuo (1978) and Pyatt, Chen, and Fei (1980), who decompose total income inequality in terms of the inequality distributions of its components. In the case of the Gini coefficient of total income, it can be decomposed as:

$$Gini(Y) = \sum_j \phi_j R_j Gini(Y_j) \tag{7}$$

where $Gini(Y_j)$ is the Gini coefficient of income source Y_j, ϕ_j is the share of income from factor j in total income and R_j is the rank correlation ratio:

$$R_j = \frac{Cov(Y_j, F_y)}{Cov(Y_j, F_j)}$$

that is, the correlation coefficient between Y_j and the ranking of Y, where F_j and F_Y are the cumulative distribution of Y_j and Y respectively. The product of the Gini coefficient of Y_j and its rank correlation ratio is usually referred to as the pseudo-Gini coefficient of income from factor j or the concentration ratio.

According to equation (7), the contribution of the Gini coefficient of earnings to income inequality is given by

$$\phi_{wit} R_{wit} Gini(W_{it})$$

As an example of this approach, Deutsch and Silber (2004) analyze the relationship between wage inequality and income inequality in a sample of 23 countries between 1983 and 1990. They present empirical evidence that R_w is close to one, with an average equal to 0.992, ranging from 0.938 in Rwanda to 1.002 in Pakistan. Therefore, differences in the rank correlation ratio R_w across countries are relatively minor when it comes to explaining differences in the contribution of wage inequality to income inequality. However, although

[11] Both Lim and Tang (2008) and Morrison and Murtin (2013) have analyzed the relationship between years of schooling and the distribution of simulated wages, but not with respect to income inequality. Conversely, Fölvári and van Leeuwen have analyzed the relationship between years of schooling and income inequality, without estimating a distribution of the Mincerian human capital income, obtaining a (non-inverted) U-curve from 1950 to 2000. Only when they instrument the Gini coefficient of years of education, taking into account the effect of the unobserved skill premium, do they find an inverted U-curve from 1950 to 2000.

wages are the most important source of income, there are significant differences across countries. The average value of ϕ_w is 0.542, ranging from 0.105 in Rwanda (where the most important income source is entrepreneurial income) to 0.940 in Japan. The evidence also shows that the share of wages is strongly correlated with the log of per capita income (equal to 0.654) whereas entrepreneurial income exhibits a negative correlation (-0.776). According to Deutsch and Silber (2004), these correlations and composition effects can explain the Kuznets curve: the rising section of the curve is mainly the consequence of the increasing share of wages, whereas the declining section is explained by the decreasing share of entrepreneurial income and the increasing role played by public transfers, which more than compensate for the rising contribution of property income inequality. Taking together the averages values ϕ_w and R_w, the weight of $Gini(W)$ as a determinant of $Gini(Y)$ is equal to 0.538 in equation (7).

In our case, we have information on the distribution of earnings for more countries (62) and years (from 1970 to 2010) than Deutsch and Silber (2004), but not for ϕ_j and R_j. To overcome this limitation, we approximate the contribution of $Gini(W_{it})$ to $Gini(Y_{it})$ by estimating the following equation:

$$Gini(Y_{it}) = \alpha + \beta_t Gini(W_{it}) + \lambda_t Gini(W_{it}) \ln y_{it} + \delta_t + u_{it} \tag{8}$$

assuming that

$$\phi_{wit} R_{wit} \simeq \beta_t + \lambda_t \ln y_{it} \tag{9}$$

where y_{it} is per capita income (in deviations from the sample mean). Note that the country heterogeneity is approximated by $\ln y_{it}$, as suggested by the results of Deutsch and Silber (2004).

Although equation (8) gives us an indirect approximation of the contribution of inequality in years of schooling to income inequality, it should be noted that OLS estimates of β and λ could be biased if the residuals in (8) are correlated with $Gini(W_{it})$. This could be the case if omitted variables (e.g., the Gini coefficients of other sources of incomes) are correlated with $Gini(W_{it})$. Additionally, measurement errors generate a bias towards zero. Nevertheless, the OLS estimates of β and λ in Deutsch and Silber's (2004) sample imply that $\phi_w R_w = 0.606$ on average, which is not statistically different to the true average weight of 0.538 in the data. This result in a small sample of very heterogeneous countries suggests that our approach to estimating the contribution of $Gini(W_{it})$ to $Gini(Y_{it})$ could be appropriate for a larger sample of countries.

We begin by estimating equation (8) assuming that $\lambda_t = 0$. We allow for time dummies (δ_t) for each period but impose the same value β for the whole sample, estimating a value of 0.565 for the coefficient of $Gini(W_{it})$, which is highly statistically significant

($t-$ratio equal to 16.3). When we allow for different values of β_t for each subperiod between 1965 and 2010, we observe that estimated values remain relatively stable, slightly below the average of 0.538 reported for the sample of Deutsch and Silber (2004). When we include the interaction term with per capita income, we obtain a very similar value of β (0.543) for the average of $\ln y_{it}$, again highly statistically significant ($t-$ratio equal to 14.8).[12]

Two main conclusions can be drawn from the results of this subsection. First, our approach produces estimates of the contribution of Gini(W_{it}) to Gini(Y_{it}) in a large sample of countries that are quite close to the values obtained by Deutsch and Silber (2004). Second, the estimated coefficients indicate that approximately each one-point change in the Gini coefficient of earnings contributes to a half-point change in the Gini coefficient of income. This effect is statistically significant and economically relevant.

5. Effect of human capital inequality on income inequality through direct channels

The effect of human capital inequality on income inequality is expected to be exerted primarily through the effect of the former on earnings inequality. However, other channels could be at work. In this section we explore whether human capital inequality has any effect on income inequality over and above its effect on earnings inequality.

To do so, we start by analyzing the effect of earnings inequality on income inequality. As shown in Table 3, earnings inequality has a positive, statistically significant, and economically meaningful effect on income inequality (column 1). The quantitative effect is substantial: a one standard deviation increase in earnings inequality (0.110) is associated with an increment of about 20 percent in the income Gini coefficient (that is, 0.064 percentage points), computed as its mean value of 0.316. In column (2), we add the human capital Gini coefficient in the set of controls. The results reveal that human capital inequality has a direct effect on income inequality over and above its effect on earnings inequality. The human capital Gini coefficient is also positive and statistically significant at the 1 percent level, even when controlling for earnings inequality. The direct effect of human capital inequality on income inequality is economically meaningful: a one standard deviation increase in the human capital Gini coefficient (0.150) is associated with a 7.7 percent increase in the income Gini coefficient, evaluated as its mean value of 0.309.

In column (3) we control for some variables related to human capital that can affect income inequality not only through earnings inequality, but also through other factors.

[12] To facilitate the comparisons of the estimated coefficient of $G(W^s)$, we have defined $\ln y$ in deviations from the sample mean. Therefore, the value of $\beta = 0.543$ is the coefficient of $G(W^s)$ when the normalized value of $\ln y$ is equal to zero.

Table 3.a
Dependent variable: *Income Inequality ($Gini^y$)*

	OLS estimates								
	Whole sample			Less Developed			Advanced		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Gini^w$	0.588[a]	0.497[a]	0.288[a]	0.440[a]	0.400[a]	0.289[a]	0.484[a]	0.457[a]	0.270[a]
	(0.035)	(0.036)	(0.044)	(0.051)	(0.051)	(0.057)	(0.051)	(0.056)	(0.047)
$Gini^h$		0.159[a]	-0.013		0.127[a]	-0.040		0.039	0.043
		(0.025)	(0.031)		(0.037)	(0.047)		(0.047)	(0.029)
Redist			-0.461[a]			-0.428[a]			-0.422[a]
			(0.062)			(0.094)			(0.059)
Fertility			0.019[a]			0.019[a]			0.024[a]
			(0.003)			(0.005)			(0.005)
Openness			0.002			-0.012			-0.034[a]
			(0.005)			(0.008)			(0.009)
FD			-0.015[b]			0.539[a]			0.018[c]
			(0.008)			(0.159)			(0.011)
Constant	0.179[a]	0.143[a]	0.242[a]	0.269[a]	0.218[a]	0.286[a]	0.172[a]	0.167[a]	0.288[a]
	(0.016)	(0.017)	(0.024)	(0.023)	(0.032)	(0.029)	(0.016)	(0.016)	(0.017)
R^2	0.505	0.550	0.652	0.314	0.353	0.443	0.385	0.388	0.679
Obs.	448	448	448	261	261	261	187	187	187
Countries	61	61	61	38	38	38	23	23	23
δ_t	Y	Y	Y	Y	Y	Y	Y	Y	Y

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

Capital and entrepreneurial incomes as well as taxes and transfers are the other components of disposable income. Whereas measures of capital inequality are not readily available for a large number of countries and periods, measures of taxes and transfers are easier to obtain. To analyze the role of taxes and transfers, we control for a measure of redistribution of income, approximated by the difference between the income Gini coefficient before and after taxes and transfers. In models of political economy, more unequal societies will demand more redistributive policies (Alesina and Rodrik, 1994; Persson and Tabellini, 1993). If the redistributive policies are implemented, their effect should be a reduction in income inequality. Since inequality of opportunities is adequately approximated by inequality in the distribution of education, a society with higher inequality in the distribution of human capital is likely to demand more rigorous redistributive policies, which at the same time influence income inequality.

Fertility is another variable highly related to human capital inequality and income inequality. For example, Moav (2005) develops a model with multiple steady states in which the dynasties within a country can converge to two alternative equilibria: one is a poverty trap characterized by high fertility rates, low investment in human capital and low income, whereas the other is described by low fertility, higher investment in offspring education and, therefore, higher income.

The relationship between international trade and inequality has been widely ana-

Table 3.b
Dependent variable: *Income Inequality ($Gini^y$)*

	Fixed Effects estimates								
	Whole sample			Less Developed			Advanced		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Gini^w$	0.052^a	0.076^a	0.075^a	0.057^a	0.085^a	0.080^a	0.041	0.046	0.049
	(0.018)	(0.018)	(0.017)	(0.021)	(0.021)	(0.020)	(0.041)	(0.041)	(0.041)
$Gini^h$		0.121^a	0.053^c		0.154^a	0.085^b		0.083^c	0.059
		(0.022)	(0.027)		(0.032)	(0.035)		(0.044)	(0.050)
Redist			-0.207^b			-0.235			-0.028
			(0.094)			(0.177)			(0.125)
Fertility			0.010^a			0.016^a			0.008
			(0.002)			(0.003)			(0.006)
Openness			0.003			0.000			-0.027^c
			(0.004)			(0.006)			(0.015)
FD			0.012			0.036			0.036
			(0.019)			(0.095)			(0.023)
Constant	0.338^a	0.282^a	0.285^a	0.379^a	0.296^a	0.331^a	0.275^a	0.250^a	0.252^a
	(0.007)	(0.012)	(0.014)	(0.009)	(0.019)	(0.017)	(0.010)	(0.017)	(0.026)
R^2 within	0.115	0.179	0.224	0.096	0.184	0.276	0.197	0.216	0.249
Obs.	448	448	448	261	261	261	187	187	187
Countries	61	61	61	38	38	38	23	23	23
δ_t	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Fixed-effects regression. Standard errors in parentheses. a, b and c are 1, 5, and 10 percent significance levels respectively.

lyzed in the literature, with special attention paid to the role of globalization in the relation between skilled and unskilled workers' wages. According to Heckhsher-Ohlin theory, countries specialize in the production of goods that intensively use the factors of production in which they are relatively abundant. Less developed economies, where unskilled labor is more abundant and cheaper, will specialize in exports of goods that are intensive in unskilled labor. The increase in the demand for unskilled labor will raise unskilled wages relative to skilled wages, reducing income inequality. In richer economies, globalization could increase income inequality, since it will increase the relative demand for skilled labor. The evidence, however, does not show that globalization is related to a reduction in income inequality in less developed countries (Goldberg and Pavenic, 2007). In fact, the effect of globalization on income inequality remains a topic of debate in the literature. Epifani and Gancia (2008) 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. Jaumote et al. (2013), however, find that trade globalization is associated with a reduction in income inequality, whereas financial globalization is associated with an increase in inequality.[13]

In column (3) we include measures of redistribution, fertility, trade openness and

[13] We also tried including other variables, such as measures of democracy and the quality of institutions, proxied by polityiv, but the coefficients of these variables were not statistically significant in any specification.

financial globalization in the set of controls.[14] As expected, greater redistribution is conducive to a reduction in income inequality. The coefficient of redistribution through taxes and transfers is negative and statistically significant at the 1 percent level. Also as expected, results indicate that higher fertility is associated with higher income inequality. The coefficient of fertility is positive and statistically significant at the 1 percent level. These results are robust across samples and hold in the fixed-effects specification as well, as shown in Table 3. Conversely, in line with the literature, the relationship between globalization and income inequality is not conclusive. Trade and financial globalization seem to have different effects on income inequality, and the effect differs depending on the level of development of the countries included in the sample and the econometric specification. Nevertheless, there is some evidence suggesting that in advanced economies, trade openness leads to less income inequality, whereas more financial globalization seems to be related to higher income inequality. As expected, when we include all the variables in the set of controls, we observe a marked reduction in the coefficient of the human capital Gini index, suggesting that these channels could explain some of the influence that human capital inequality exerts on income inequality.

6. Conclusions

Does a reduction in human capital inequality translate into a reduction in income inequality? The answer to this question has been a topic of debate in the literature. Whereas some studies find a positive correlation between the two inequality indicators, other studies have cast doubt on this result. Differences in the sample, measures of inequality and econometric techniques could explain some of the discrepancies found in the empirical literature. This paper addresses the relationship between human capital inequality and income inequality from a comprehensive perspective and examines the role of earnings inequality in the interaction between the two indicators.

We start the analysis by exploring the relationship between human capital inequality and wage inequality, using an improved data set on human capital inequality and a novel data set on earnings inequality. We find an inverted U-shaped relationship between these two inequality indicators. On average, the Gini coefficient for labor earnings inequality reaches its maximum when the share of illiterates is about 40 percent, which corresponds to an average of 5.5 years of schooling. Nevertheless, we show significant differences across countries regarding the turning point where the relationship between

[14] The results in this section should be interpreted as correlations and not evidence of causal effects. In fact, some of the channels analyzed are bidirectional. For example, in fertility models with a trade-off between quality and quantity of children, higher human capital/income inequality is associated with higher differential fertility among individuals with different human capital/income levels. At the same time, higher differential fertility among individuals with different levels of schooling will influence the distribution of human capital and income.

human capital inequality and earnings inequality becomes positive. Thus, a share of illiterates of around 40 percent is a world average, but not a universal indicator that can be directly applied to every country. This result is consistent with the hypothesis that in an economy with two population groups—low and high educational level—a transfer of workers from the former to the latter raises the inequality of earnings, up to the point where the high-education-level group reaches a certain share. Our results confirm the inverted U-shaped relationship with regard to the share of illiterates.

Along with the development process in dual economies, an additional force that may blur the relationship between human capital and earnings inequality is skill-biased technological change. In this vein, we find evidence confirming that, despite the increase in the relative supply of skilled workers, labor earnings inequality has increased by an average of 0.62 percent each year in our sample period.

We then estimate the average contribution of earnings inequality to income inequality. We find that the estimated coefficient of earnings inequality is statistically significant, relatively stable and economically relevant: approximately each one-point change in the Gini coefficient of earnings contributes on average to a half-point change in the Gini coefficient for income.

Finally, we show that human capital inequality influences income inequality in other ways besides its effect through earnings inequality. We find a positive and direct effect of human capital inequality on income inequality, even when controlling for the Gini of earnings. Most of the direct effect is explained by channels related to redistributive policies, fertility, trade openness and financial globalization. Overall, earnings inequality and the direct channels explain about 65 percent of the variation in income inequality. The remaining 35 percent could be explained by other forces that have driven income inequality upwards.

The evidence presented in this paper is highly relevant for development policies. Many governments have made major efforts to eradicate illiteracy rates, but these policies have not been accompanied by a more even distribution of income, due to the presence of different offsetting forces. However, this evidence does not imply that educational policies have failed to reduce poverty or improve the earnings and standard of living of hundreds of millions through better education. On the contrary, eradicating illiteracy and ensuring the completion of primary schooling are necessary conditions for the subsequent improvement in per capita income and inequality, showing that there is no trade-off between them. Better education is crucial in order to increase average earnings per worker, to avoid the negative effects of skill-biased technological change and to offset other driving forces that may contribute to greater income inequality.

7. References

Acemoglu, D. and D. Autor (2012). "What Does Human Capital Do? A Review of Goldin and Kazt˙s The Race Between Education and Technology." *Journal of Economic Literature*, Vol. 50(2), 426-463.

Ahluwalia, M. S. (1976). "Income Distribution and Development: Some Stylized Facts." *American Economic Review*, Vol. 66(2), 128-35.

Alesina, A. and Rodrik, D. (1994). "Distributive Politics and Economic Growthı, *Quarterly Journal of Economics,* vol. 109, pp. 465-90.

Anand, S. and S.M.R. Kanbur (1993). "The Kuznets Process and the Inequality-Development Relationship." *Journal of Development Economics*, Vol. 40, 25-52.

Atkinson, A. B. and A. Brandolini (2001). "Promise and Pitfalls in the Use of 'Secondary' Data Sets: Income Inequality in OECD Countries as a Case Study." *Journal of Economic Literature*, 39, 771-99.

Barro, R. J. and J. W. Lee (2001): "International Data on Educational Attainment Updates and Implications." *Oxford Economic Papers*, no. 3, 541-63.

Barro, R. and J-W Lee (2013). "A New Dataset of Educational Attainment in the World, 1950-2010." *Journal of Development Economics*, 104, 184–198.

Becker, G. S. and B. R. Chiswick (1966). "Education and the Distribution of Earnings," *American Economic Review*, Vol. 56 (1), 358-69.

Card, D. and T. Lemieux (2001). "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *Quarterly Journal of Economics*, Vol. 116 (2), 705-46.

Castello, A. and R. Doménech (2002): "Human Capital Inequality and Economic Growth: Some New Evidence." *The Economic Journal*, 112 (March), 187-200.

Checchi, D. and C. García-Peñalosa (2010): "Labour Market Institutions and the Personal Distribution of Income in the OECD." *Economica*, 77(307), 413-450.

Chiswick, Barry R. (1971). ˇEarnings Inequality and Economic Development,ı *Quarterly Journal of Economics*, vol. 85(1), 21–39.

Cohen, D. and M. Soto (2007). "Growth and Human Capital: Good Data, Good Results." *Journal of Economic Growth*, 12(1), 51-76.

Cowell, F. A. and C. V. Fiorio, 2011). "Inequality Decompositions - A Reconciliation." *Journal of Economic Inequality*, 9, 509–528.

Deininger, K. and L. Squire (1996). "A New Data Set Measuring Income Inequality." *World Bank Economic Review*, 10, 565-91.

De Gregorio, J., and J. W. Lee (2002). "Education and Income Distribution: New Evidence from Cross-Country Data." *Review of Income and Wealth*, Vol. 48(3), 395–416.

de la Fuente, A. and R. Doménech (2006). "Human Capital in Growth Regressions: How Much Difference Does Data Quality Make." *Journal of the European Economic Association*, 4(1), 1-36.

de la Fuente, A. and R. Doménech (2015). "Educational Attainment in the OECD, 1960–2010. Updated Series and a Comparison with Other Sources." *Economics of Education Review*, 48, 56-74.

Deutsch, J. and J. Silber (2004). "Measuring the Impact of Various Income Sources on the Link Between Inequality and Development: Implications for the Kuznets curve." *Review of Development Economics*, 8(1), 110-127.

Epifani, P. and G. Gancia (2008). "The Skill Bias of World Trade," *The Economic Journal*, vol. 118, 927-60.

Fei, J. C. H., G. Ranis, and S. W. Y. Kuo (1978). "Growth and the Family Distribution of Income by Factor Components." *The Quarterly Journal of Economics*, 92(1), 17-53.

Fields, G. S. (1979). "A Welfare Economic Approach to Growth and Distribution in the Dual Economy." *The Quarterly Journal of Economics*, 93(3), 325-353.

Fields, G. S. (1993). "Inequality in Dual Economy Models." *The Economic Journal*, 103(420), 1228-1235.

Földvári, P., and B. van Leeuwen (2011). ˇShould Less Inequality in Education Lead to a More Equal Income Distribution?ı *Education Economics*, 19 (5), 537–554.

Goldberg, P.K. and N. Pavcnik (2007). "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Perspectives*, Vol. XLV, 39-82.

Hammar, O. and D. Waldenström (2020). ˇGlobal Earnings Inequality: 1970-2018,ı *Economic Journal*, 130 (November), 2526–2545.

Jaumotte, F., S. Lall and Ch. Papageorgiou (2013). "Rising Income Inequality: Technology, or Trade and Financial Globalization?" *IMF Economic Review*, Vol. 61(2), 271-309.

Karabarbounis, L. and B. Neiman (2013). "The Global Decline of the Labor Share." *The Quarterly Journal of Economics*, 129(1), 61-103.

Katz, L. F. and K. M. Murphy (1992). "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, vol. 107 (1), 35-78.

Knight, J. B. (1976). "Explaining Income Distribution in Less Developed Countries: A Framework and an Agenda," *Oxford Bulletin of Economics and Statistics*, 38(3), 161-177.

Knight, J. B., and R.H. Sabot (1983). "Educational Expansion and the Kuznets Effect." *The American Economic Review*, 73(5), 1132-1136.

Kuznets, S. (1955). "Economic Growth and Income Inequality," *American Economic Review*, vol. 45(1), 1-28.

Lee, J.W. and H. Lee (2018). ˇHuman Capital and Income Inequality,ı *Journal of the Asia Pacific Economy*, vol. 23(4), 554-583.

Lim, A. S. K., and K. K. Tang (2008). "Human Capital Inequality and the Kuznets Curve." *The Developing Economies*, 46(1), 26-51.

Moav, O. (2005). ˇCheap Children and the Persistence of Povertyı, *Economic Journal,* 115, 88-110.

Mincer, J. (1974). *Schooling, Experience and Earnings*. Columbia University Press.

Morrisson, C. and F. Murtin (2013). "The Kuznets curve of human capital inequality: 1870–2010." *Journal of Economic Inequality,* 11, 283–301.

Park, K. H. (1996). "Educational expansion and educational inequality on income distribution." *Economics of Education Review,* 15, 51-58.

Persson, T. and G. Tabellini (1994). "Is Inequality Harmful for Growth? Theory and Evidence". *American Economic Review,* 84, 600-21.

Piketty, T. and G. Zucman (2014). ˇCapital is Back: Wealth-Income Ratios in Rich Countries 1700–

2010,ı *Quarterly Journal of Economics*, Vol. 129(3), 1255-1310.

Pyatt, G., C. Chen and J. Fei (1980). "The distribution of income by factor components." *Quarterly Journal of Economics*, 95, 451-474.

Ram, R. (1984). "Population Increase, Economic Growth, Educational Inequality, and Income Distribution: Some Recent Evidence." *Journal of Development Economics*, Vol. 14, 419–28.

Robinson, S. (1976). "A Note on the U Hypothesis Relating Income Inequality and Economic Development." *The American Economic Review*, 66(3), 437-440.

Roser, M. and J. C. Cuaresma (2016). ˇWhy is Income Inequality Increasing in the Developed World?ı *Review of Income and Wealth*, 62(1), pp. 1-27.

Sylwester, K. (2002). "Can education expenditures reduce income inequality?" *Economics of Education Review*, 21, 43-52.

Winegarden, C. R. (1979). ˇSchooling and Income Distribution: Evidence from International Data,ı *Economica*, 46, 83–7.

8. Online Appendix A1. The duration of levels of education

Barro and Lee (2013) provide data on total average years of schooling (TYR). Years of education are available for different levels of schooling, namely primary (PYR), secondary (SYR) and tertiary (HYR) education. The dataset also provides information on the highest level attained, disaggregated into total and complete levels. For example, for the population aged 15 years and over, the attainment levels include the share of population with total primary (PRI), primary completed ($PRIC$), total secondary (SEC), secondary completed ($SECC$), tertiary ($HIGH$), and tertiary completed ($HIGHC$). We compute incomplete attainment levels by subtracting the complete value from the total attainment in each educational level.

The calculation of the Gini coefficient requires the duration of each level of education (x_i). We use Barro and Lee˙s (2013) data set to compute duration as follows:

$$HYR = DURH * HIGH \tag{10}$$

$$DURH = \frac{HYR}{HIGH} \tag{11}$$

where $DURH$ stands for the duration in years of tertiary education. Expression (10) can be disaggregated into complete and incomplete education. Thus, the average years of schooling of tertiary education can be rewritten in terms of both levels of education:

$$HYR = DURH^{INC} * HIGH^{INC} + DURH^{C} * HIGH^{C} \tag{12}$$

where the superscripts INC and C account for incomplete and complete education respectively. As we do not have information on the duration of each level, we assume the duration of incomplete levels to be half that of the corresponding complete level of schooling. Rearranging the above expressions gives the duration of completed tertiary education,

$$DURH^{C} = \frac{HYR}{[HIGH^{INC}/2] + HIGH^{C}} \tag{13}$$

A similar procedure is used to compute the duration of secondary education

$$DURS = \frac{SYR}{SEC + HIGH} \tag{14}$$

$$DURS^C = \frac{SYR}{[SEC^{INC}/2] + [SEC^C + HIGH]} \tag{15}$$

and primary schooling

$$DURP = \frac{PYR}{PRI + SEC + HIGH} \tag{16}$$

$$DURP^C = \frac{PYR}{[PRI^{INC}/2] + [PRI^C + SEC + HIGH]} \tag{17}$$

The additional information provided by the larger number of educational levels makes the new Gini coefficient more precise than previous versions.

9. Online Appendix A2. Summary statistics of human capital and income Gini coefficients

Table A.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 0.676, followed by Sub-Saharan African (SSA) countries (average $Gini^h$ equal to 0.663), and the Middle East and the North African (MENA) region (average $Gini^h$ equal to 0.615). 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 most evenly distributed. Lying in between these extremes, the Latin American and Caribbean countries (LAC) and the East Asian and the Pacific region (EAP) have average Gini coefficients of 0.421 and 0.452, respectively.

Table A.1
Summary Statistics

	$Gini^h$										
	Countries	*Mean*	*Std. Dev.*	*Min*	*Max*	$Gini^h_{1950}$	$Gini^h_{2010}$	$3^{rd}Q^h_{1950}$	$3^{rd}Q^h_{2010}$	$1^{st}/5^{th}Q^h_{1950}$	$1^{st}/5^{th}Q^h_{2010}$
Whole sample	146	0.472	0.235	0.050	0.998	0.615	0.312	0.163	0.377	0.055	0.198
Advanced Economies	24	0.274	0.116	0.088	0.853	0.325	0.203	0.370	0.465	0.216	0.324
East Asia and the Pacific	19	0.452	0.183	0.153	0.936	0.644	0.290	0.121	0.403	0.005	0.174
Europe and Central Asia	20	0.275	0.131	0.050	0.668	0.414	0.152	0.296	0.500	0.101	0.443
Latin America and the Caribbean	25	0.421	0.161	0.116	0.929	0.542	0.280	0.201	0.403	0.032	0.198
Middle East and North Africa	18	0.615	0.225	0.193	0.998	0.830	0.366	0.036	0.339	0.001	0.090
South Asia	7	0.676	0.209	0.187	0.990	0.813	0.454	0.043	0.255	0.000	0.039
Sub-Saharan Africa	33	0.663	0.196	0.180	0.967	0.827	0.465	0.021	0.250	0.000	0.063

Table A.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

As explained in the main text, we measure income inequality through the net income Gini coefficient taken from the Standardized World Income Inequality Database (SWIID), version SWIID v8.1, which uses a custom missing-data algorithm to standardize WIID from the LIS data set. The data include 96 countries with observations from 1985 to 2010. Table A. 2 displays the mean values of the income and human capital Gini coefficients for several regions in the world.

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ENQUIRIES TO:
BBVA Research: Azul Street. 4. La Vela Building – 4th and 5th floor. 28050 Madrid (Spain).
Tel.:+34 91 374 60 00 y +34 91 537 70 00 / Fax:+34 91 374 30 25
bbvaresearch@bbva.com www.bbvaresearch.com