Human Capital Inequality and Economic Growth: Some New Evidence

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Abstract

This paper provides a measure of human capital inequality for a broad panel of countries. Taking attainment levels from Barro and Lee (1996), we obtain Gini coefficients and the distribution of education by quintiles for 116 countries over five-year intervals from 1960 to 1990. Using this new cross-country data on human capital inequality we find the following results: (1) differences in the distribution of human capital across countries are greater than within each country, (2) with the exception of OECD, all countries have tended to reduce the inequality in human capital distribution, (3) in general, societies with a higher stock of human capital are also the societies with the best distribution in education, and (4) human capital inequality measures provide better results than income measures in the estimation of growth and factor accumulation equations.

JEL classification: I29; O15; 050

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1. Introduction

How is inequality generated? How does inequality evolve over time? How does inequality influence other variables such as economic growth? Numerous researchers have tried to answer these questions over the years. Initially, economists paid attention to factors that determine income inequality. In particular, Kuznets (1955) analysed the influence of economic growth upon the evolution of the distribution of income. Using both cross-country and time series data, Kuznets (1963) found an inverted U-shaped relation between income inequality and GNP per capita. This result was interpreted as describing the evolution of the distribution of income over the transition from rural to industrial economies. The work on the Kuznets curve deals with the question of how the level of income affects income distribution. In contrast, the more recent literature addresses the question of how income distribution affects the growth of income, that is, it focuses on the potential effects of inequality on economic growth through different channels.[1]

Nevertheless, the absence of data on the distribution of wealth for a sufficient number of countries and for sufficiently long periods forces researchers to use different proxies in empirical studies. The most common approach is to use data on income inequality as a proxy for wealth inequality. On other occasions, the distribution of wealth is proxied by the distribution of land. For example, Alesina and Rodrik (1994) use the Gini coefficient of land distribution as a proxy of a measure of wealth distribution, whereas Deininger and Squire (1998) include land inequality along with income inequality to analyse the relationship between initial inequality in the assets distribution and long-term growth. They find that initial land inequality is more significant than income inequality in the estimation of growth equations.

However, income or land inequality can be insufficient measures of wealth inequality since other variables such as human capital are important determinants of development. Thus, in some models that analyse the relationship between inequality and economic growth, the role played by human capital endowment is very important. For instance, Glomm and Ravikumar (1992) examine the implications of public investment in human capital on growth and the evolution of income inequality in an economy in which individuals have different income/skill levels. In their overlapping generation model, agents within a generation are only differentiated by the stock of human capital of their parents and, since income is fully determined by human capital, the distribu-

[1] We can distinguish three approaches in this literature given by three different mechanisms: the effects of income inequality on fiscal policy (Alesina and Rodrik, 1994, and Persson and Tabellini, 1994), the effects on sociopolitical instability (Alesina and Perotti, 1996), and finally, the effects on human capital accumulation (Galor and Zeira, 1993).

tion of income is given by the distribution of human capital.[2] Nevertheless, due to the scarcity of available data of human capital inequality, little attention has been devoted to human capital distribution in empirical studies. Some exceptions are Birdsall and Londoño (1997) or López, Thomas and Wang (1998). Using a sample of 43 countries, Birdsall and Londoño (1997) analyze the effect of initial inequalities in the distribution of income, land and of human capital on economic growth. In their regression, they use as independent variables the capital accumulation rate and some initial conditions such as income level, educational level, income inequality, land inequality and education inequality. They obtain a negative effect from land and education inequality on aggregate growth. Moreover, this negative effect is stronger when the dependent variable is the income growth rate of the poorest. Nevertheless, in this paper, whereas income and land inequality are measured by a Gini coefficient, education inequality is measured by the standard deviation of years of education. As it is well knonw, the problem with the standard deviation is that it is an absolute measure of dispersion thus it does not control for differences in the mean of the distribution.

López, Thomas and Wang (1998) use a panel data from 12 Asian and Latin American countries from 1970 to 1995. They analyse the effects of human capital accumulation and human capital inequality on income per capita and on economic growth. They show that human capital inequality, measured by the coefficient of variability of education and the standard deviation of the log of education, tends to have a negative impact on per capita income in most countries. On the other hand, although their results indicate that the positive effect of human capital accumulation on economic growth is greater under competitive and open market conditions, in their regressions there is no evidence of a negative and significant effect of human capital inequality, measured by the coefficient of variability, on economic growth.

The main objective of this paper is to provide indicators of human capital inequality for a large sample of countries and years. In particular, using the information contained in Barro and Lee's (1996) data set, we distribute attainment levels by quintiles that allow us to obtain a Gini coefficient of human capital. The main advantage of our indicators is that complements the information provided by income inequality measures.

As is well known, income distribution data suffer from several problem. Apart from the limitations related to their quality, the main problems arise with the different definitions of income used to measure inequality.[3] The problems in the homogeneity of

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[2] Saint Paul and Verdier (1992) or Lee and Roemer (1998), among others, present models in which income distribution is mainly determined by human capital distribution.

[3] The three main differences in these definitions are given by the distinction between gross and net income, income and expenditure and, finally, per capita and household income.

these definitions can reduce significantly the size of the samples in international and intertemporal comparisons. Although the income distribution data set of Deininger and Squire (1996) has represented a significant improvement in coverage and quality compared with previous data sets, in our oppinion there is room for improvements in other inequality indicators, especially in developing countries where income inequality data are more scarce. Our measures of human capital inequality are only restricted by the coverage and quality of Barro and Lee's figures, which refer to 116 countries over five-year intervals from 1960 to 1990.

Using our new measure of human capital inequality we analyse its relationship with economic growth. The main findings show that human capital inequality measures provide better results than income measures. Moreover, the influence of human capital inequality on economic growth rates is given through the negative effect of human capital inequality on the accumulation of physical and human capital.

The structure of this paper is as follows. The next section presents the procedure used to construct a human capital Gini coefficient using Barro and Lee's variables. Section 3 compares the information contained by different measures of inequality as the Gini coefficient and educational shares by quintiles. Section 4 analyses the distribution across countries of the Gini coefficient of human capital inequality and its evolution from 1960 to 1990. Section 5 presents preliminary evidence on the relationship between our measure of human capital inequality and other variables such as the income inequality, human capital levels, life expectancy or public spending in education, among others. Section 6 analyses the relationship between human capital inequality and economic growth. Finally, Section 7 contains the conclusions reached.

2. Measuring Human Capital Inequality

This section describes how to obtain a new measure of human capital inequality for a broad cross section of countries. We take schooling figures from Barro and Lee (1996) to construct a standard representation of inequality: the Gini coefficient. The choice of this index to analyse inequality in the distribution of human capital is mainly due to the fact that it is the one normally used in international comparisons of income distribution. Nevertheless, as has been pointed out by Deininger and Squire (1996) among others, it is difficult to characterise inequality by such a simple measure. For example, a change in the index may be explained by educational redistribution from the top quintile to the middle one or by an increase in the share of education attained by the bottom quintile at the expense of the middle educated class. For this reason, to extend the information provided by the Gini index we also report figures of the distribution of education by quintiles.

The Gini coefficient is based on the Lorenz curve which, in our case, relates the share of population compared to the share of schooling years attained. The expresion to calculate the Gini coefficient can be derived from alternative formulae. One such way which brings out the Gini definitions is:

$$G^h = \frac{\sum_{i=1}^{n} (p_i - q_i)}{\sum_{i=1}^{n} p_i} \tag{1}$$

where p_i is the cumulative population and q_i is the cumulative years of schooling attained by the i-th quintile. In particular, q_i combines the information of attainments levels and average years of primary, secondary and tertiary education of the population aged 15 and over, from the Barro and Lee (1996) data set.

To calculate these coefficients we divided the population in five quintiles and then we calculate the percentage of schooling years attained for the 20, 40, 60, 80 and 100 per cent of the population. Table 1 shows two examples that illustrate how the Gini coefficient has been obtained. The two countries in this example are Mali and Finland in 1960 which are at the extremes of the distribution. The Lorenz curves for these two countries are represented in Figure 1. The low Gini index of Finland implies that the Lorenz Curve for this country is very close to the diagonal line, whereas the Gini coefficient of Mali, which it is equal to 1.00, is a good example of absolute inequality.

The Gini coefficient takes values from 0 to 1: the higher the index the bigger the inequality in the distribution of human capital. A Gini coefficient equal to one indicates that at least 80 per cent of the population has no schooling, and that all education is concentrated in the remaining 20 per of the population concentrates all education. This is the case, for example, of some Sub-Saharan African countries. On the other hand, a Gini coefficient equal to zero would represent the case where the attainment level in each quintile is the same. Basic descriptive statistics of the Gini coefficients for the whole sample are shown in Table 2. All countries for which human capital variables are available have been classified in seven different groups: Sub-Saharan Africa, Middle East and North Africa, South Asia, East Asia and Pacific, Latin America, Eastern Europe, and OECD and High Income countries.[4] The data set includes 116 countries in the world from 1960 to 1990, so there is a total of 778 observations.

The overall sample mean is 0.521 and the standard deviation is 0.289. The second and third columns of the table illustrate that South Asia countries are the group that, on average, have more inequality in the distribution of human capital as well as the largest

[4] A similar classification is also used by Deininger and Squire (1996) and Barro and Lee (1996).

Table 1
Two examples of the computation of the Gini coefficient

	h	x_h	n_h	s_i	p_i	$\widetilde{x}_i$	u_i	q_i	$p_i - q_i$	G^h
Mali (1960)	0	0	94.2	20	20	0	0	0	20	1.000
	1	5.9	5.5	20	40	0	0	0	40	
	2	3.3	0.1	20	60	0	0	0	60	
	3	5.0	0.2	20	80	0	0	0	80	
				20	100	36.0	36.0	100.0	0	
Finland (1960)	0	0	0.6	20	20	140.3	140.3	18.5	1.5	0.055
	1	7.2	87.5	20	40	144.6	284.9	37.7	2.3	
	2	2.1	7.6	20	60	144.6	429.5	56.8	3.2	
	3	2.9	4.2	20	80	144.6	574.1	75.9	4.1	
				20	100	182.1	756.2	100.0	0	

Definitions. h: education level (no schooling (0), primary (1), secondary (2) and tertiary (3)); x_h: average schooling years of each education level; n_h: percentage of no schooling, primary, secondary and higher schooling attained by population of 15 years and over; s_i: population divided in five intervals, p_i: cumulative population; $\widetilde{x}_i$: average schooling years attained by each interval of population; u_i= $\sum_{j=1}^{i} x_j$; q_i=$\frac{u_i}{u_5}$100). As an example, the value of $\widetilde{x}_5$ for Mali in 1960 is given by

$$\widetilde{x}_5 = n_3(x_1 + x_2 + x_3) + n_2(x_1 + x_2) + n_1 x_1 + (20 - n_1 - n_2 - n_3)0 = 36.0$$

Using Barro and Lee's variables we define $x_1 = PYR15/(PRI15 + SEC15 + HIGH15)$, $x_2 = SYR15/(SEC15 + HIGH15)$ and $x_3 = HYR15/HIGH15$.

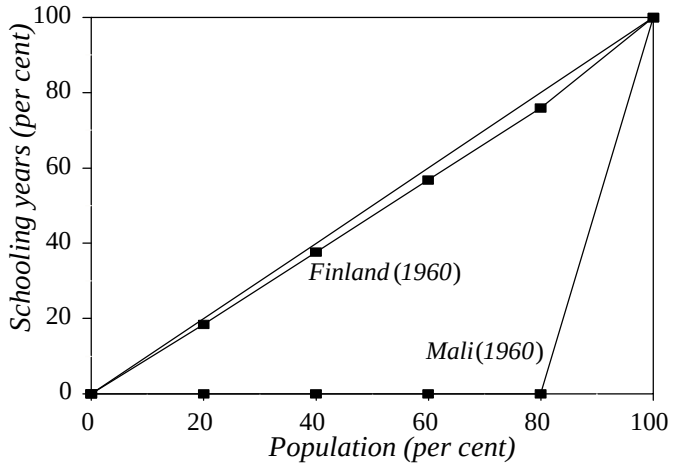

Figure 1: *Human capital inequality. Lorenz curve for Finland and Mali in 1960.*

dispersion among their sample. The two extremes in this world area are Afghanistan, with a Gini coefficient equal to 1.00 for all the periods, and Sri Lanka, with an average Gini coefficient equal to 0.416.[5] The Middle East and North African region exhibits an average Gini coefficient equal to 0.775 ,Israel being the country with a more equalitarian distribution of human capital (0.257). This region is closely followed in terms of human capital inequality by Sub Saharan African countries with an average Gini coefficient equal to 0.774. Again, we find in this group countries with absolute human capital inequality during the whole period (e.g.: Mali and Niger), and more equalitarian countries such as Lesotho and Mauritius, with a Gini coefficient equal to 0.417 and 0.433 respectively.

The countries with a more equalitarian distribution of human capital are those in Eastern Europe with a mean of 0.182. In this group, Yugoslavia is the only country with a Gini coefficient above 0.300. This region is followed by OECD countries which have, on average, a Gini coefficient equal to 0.251. The countries in the north of Europe as well as Australia and New Zealand have the lowest Gini coefficients. On the opposite side, we find Portugal and Turkey with Gini coefficients equal to 0.560 and 0.669, respectively. The sixth column indicates that all groups of countries, with the exception of OECD countries, have decreased the inequality in the distribution of human capital. The

[5] See the Appendix for complete country results.

Table 2
Average human capital Gini coefficient by groups of countries

	Mean	std.dev.	max	min	$\Delta \ln G^h$	H	G^y
Sub Saharian Africa	0.774	0.182	1.000	0.342	-0.041	2.134	0.447
Middle East & North Africa	0.775	0.177	1.000	0.205	-0.071	3.045	0.408
South Asia	0.846	0.220	1.000	0.330	-0.034	2.162	0.341
East Asia & Pacific	0.484	0.198	1.000	0.187	-0.085	5.052	0.362
Latin America	0.447	0.175	1.000	0.145	-0.029	4.491	0.502
Eastern Europe	0.182	0.072	0.359	0.092	-0.025	7.971	0.260
OECD & High Income	0.251	0.139	0.766	0.055	0.027	7.395	0.332
Total	0.521	0.289	1.000	0.055	-0.032	4.498	0.379

H is average schooling years of the population aged 15 and over (variable TYR in Barro and Lee data set). G^y is the average Gini coeficient on income from Deininger and Squire (1996), for available countries and years in each geographic area.

largest reduction has taken place in the East Asia and Pacific region, especially in countries such as Indonesia, Korea or Taiwan. In the case of Taiwan, for example, Tallman and Wang (1994) noticed the important role played by the government in increasing the quality of labour force and reducing illiteracy from the early 50s.

Finally, if we compare our human capital inequality indicator with the average Gini coefficient on income inequality from Deininger and Squire (1996), we can appreciate that whereas Latin American countries present the worst distribution of income, they are ranked as the third group of countries in terms of a better distribution of human capital. On the other hand, the South Asia countries present the biggest human capital inequality in opposition to an income Gini of less than 0.35. Eastern Europe followed by OECD are the regions with less inequality in the distribution of both income and education.[6]

3. Educational Shares by Quintiles

As we have mentioned before, to improve the information provided by the Gini coeffi-

[6] Related to human capital inequality, a similar ranking is obtained by Birdsall (1998) when the coefficient of variation is used as a measure of human capital inequality. Nevertheless, on average, she gets lower human capital inequality in East Asia & Pacific than in Latin America countries. This difference may be due to the different countries included in the groups. For example, we include Burma and Papua New Guinea in the East Asia & Pacific region. Since these countries have high human capital inequality, their inclusion increases the average value of the group.

cient, we have also computed the distribution of education by quintiles, in line with some of the most recent contributions to the analysis of the relationship between the distribution of income and economic growth. For instance, Persson and Tabellini (1994) use the third quintile as a measure of equality, Perotti (1996) combines the third and fourth quintile to capture the notion of ``middle class'', and Deininger and Squire (1996) calculate the top to the bottom quintile ratio as a measure of inequality.

The correlations between different measures of human capital inequality are shown in Table 3.[7] The table shows a strong negative correlation between the Gini index and the different quintiles. In terms of the definitions we have used in Table 1, we have that

$$Q_i = \frac{u_i}{u_5}.$$

The correlation is greater than 0.9 between the Gini index and the second, third and fourth quintiles. In particular, the greatest correlation is with the third quintile with a coefficient close to one, whereas the quintile with the smallest correlation is the first one. The indicator of equality, the ratio of the bottom quintile to the top one ($\widetilde{x}_1/\widetilde{x}_5$), is the measure with the lowest correlation, although it is still very high in absolute terms. These results reveal that the human capital Gini coefficient seems to be a good indicator of the education attained by 60 per cent of the population or, in terms of income distribution, by the ``middle class''. However, to analyse what happens in the tails of the distribution, it would be better to use the first and fifth quintiles directly or a combination of them.

In spite of the high correlation between the Gini coefficient and the different quintiles, changes from 1960 to 1990 in the Gini coefficient may be associated with different movements in quintiles. Thus, to get additional information that is not captured in our aggregate measure of inequality, Table 4 shows educational shares of the lowest, middle and highest quintiles by groups of countries during the period 1960-1990.

In Table 4 we can observe some examples that illustrate the value of combining the aggregate measure of inequality and information on educational shares. Despite South Asia countries showing on average a bigger Gini coefficient than Sub-Saharan African countries, the lowest 20 per cent of the population receive more education in the former group than in the latter. However, the third quintile is bigger in Sub-Saharan African countries.

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[7] Deininger and Squire (1996) compute the *Top20/Bottom20* ratio as a measure of income inequality. Nevertheless, as many countries have a high percentage of illiteracy, the lowest 20 per cent of population has no education. To avoid divisions by zero, we compute the inverse of this ratio, which can be interpreted as a measure of equality.

Table 3
Correlation matrix between different measures of inequality

	G^h	Q_1	Q_2	Q_3	Q_4	Q_1/Q_5
G^h	1					
Q_1	-0.80	1				
Q_2	-0.93	0.89	1			
Q_3	-0.98	0.77	0.92	1		
Q_4	-0.94	0.61	0.76	0.90	1	
Q_1/Q_5	-0.79	0.99	0.87	0.74	0.60	1

In general, almost all countries have increased the percentage of education received by the third quintile and reduced the percentage of education received by the top quintile. In particular, the greater change took place in Middle Eastern and North African countries, where the top quintile in the sixties was 0.822 which reduced to 0.481 in the nineties. In addition, the education received by the third quintile has increased from 0.059 in the sixties to 0.226 in the nineties. However, in OECD countries the education received by 60 per cent of the population has been reduced in relative terms. The behavior of the lowest quintile has also been quite different. While OECD countries display a reduction in this indicator from 1960 to 1990 and Africa and South Asia during the eighties, Eastern Europe, Latin America and East Asia Pacific countries have increased the percentage of education in the bottom quintile of the population.

4. Variations Within and Across Countries

This section explores the variability of the Gini coefficient on human capital across and within countries. Li, Squire and Zou (1998), using the Deininger and Squire (1996) data set, find that income inequality is relatively stable within countries but it varies significantly among countries. This section tries to answer the following questions: How strong are the differences in human capital inequality among countries? Have these differences persisted over time or have they been reduced?

Looking at Table 2, we can observe significant differences in human capital inequality among groups of countries. African and South Asian countries have, on average, more inequality than East European and OECD countries. Moreover, the standard deviation of the means of the 116 countries (0.289) is greater than any of the standard deviations of the within-country Gini coefficient for each country. This preliminary evidence indicates that, over the period under study, the variability of the Gini index is greater among countries than within each country.

Table 4
Educational shares of the lowest, middle and high quintile 1960-1990

	Average	1960s	1970s	1980s	1990s
	Lowest Quintile				
Sub Saharan Africa	0.0005	0.0000	0.0000	0.0014	0.0012
Middle East North Africa	0.0053	0.0030	0.0077	0.0078	0.0074
South Asia	0.0038	0.0000	0.0000	0.0090	0.0084
East Asia Pacific	0.0249	0.0132	0.0182	0.0372	0.0421
Latin America	0.0386	0.0238	0.0380	0.0484	0.0497
Eastern Europe	0.1162	0.1104	0.1126	0.1195	0.1283
OECD & High Income	0.1070	0.1123	0.1071	0.1042	0.1019
	Third Quintile				
Sub Saharan Africa	0.1036	0.0719	0.0893	0.1236	0.1459
Middle East North Africa	0.0957	0.0586	0.0790	0.1368	0.2259
South Asia	0.0616	0.0509	0.0553	0.0628	0.0931
East Asia Pacific	0.3059	0.2422	0.2966	0.3427	0.3761
Latin America	0.3329	0.3059	0.3327	0.3480	0.3566
Eastern Europe	0.4982	0.4971	0.4950	0.4960	0.5115
OECD & High Income	0.4479	0.4545	0.4405	0.4479	0.4497
	Top Quintile				
Sub Saharan Africa	0.6693	0.7298	0.6874	0.6323	0.5745
Middle East North Africa	0.6734	0.8220	0.6480	0.5653	0.4808
South Asia	0.7844	0.8552	0.8210	0.7524	0.6335
East Asia Pacific	0.4261	0.5062	0.4348	0.3843	0.3573
Latin America	0.4158	0.4446	0.4293	0.3894	0.3841
Eastern Europe	0.2769	0.2851	0.2820	0.2705	0.2627
OECD & High Income	0.3152	0.3217	0.3205	0.3087	0.3048

Nevertheless, this evidence does not mean the dispersion of the Gini coefficient has remained stable in time. To study the possible existence of a general within-country time trend during the period 1960-1990, as well as the existence of country specific effects, we consider the following simple linear trend model:

$$G_{it}^{h} = \alpha_i + \beta d_t + u_{it}$$

where i is the number of countries and d is a trend. To analyze the existence of country specific effects, we have tested the following hypothesis:

$$H_0 : \alpha_1 = ... = \alpha_n$$

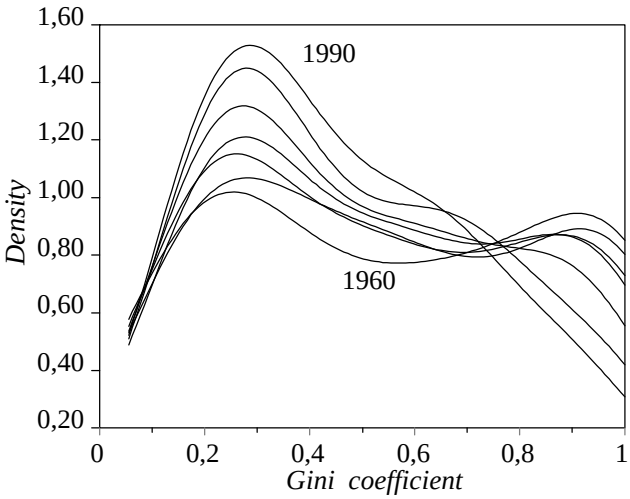

Figure 2: *Density function of the Gini coefficient: 1960-1990.*

If we can accept this hypothesis, then country specific effects for each country are non-statistically significant for the whole sample. As expected, the results shown in Table 5 indicate that the null hypothesis is rejected and, as we can also observe, the coefficient for a general trend is negative and significant. Therefore, the differences in Gini coefficients across countries are important and, in general, countries have tended to reduce the inequality in human capital distribution.

The preceding exercise shows how the mean of this indicator has evolved over time, but we want also to analyse how the dispersion and relative position for each country has changed from 1960 to 1990. The easiest way to test the constancy in the dispersion of the Gini coefficient is through a time plot of its standard deviation. As popularised by Barro and Sala-i-Martin, if the dispersion of cross-section levels dismisses over time, we can say that there is *σ-convergence*.[8] Nevertheless, this measure is not enough to characterise the distribution when it is not a normal one. In particular, the Jarque-Bera statistic rejects the null hypothesis of normality of the distribution of the Gini coefficient. For this reason, in Figure 2 we have represented non-parametric estimations of the density function of G^h using a standard normal kernel for the sample of countries in each available year. As we can see, the distribution of G^h in 1960 clearly shows two modes, but slowly

[8] See, for instance, Barro and Sala-i-Martin (1992).

Table 5
Exclusion of country specific effects

β	-0.22
	(--16.09)
F test of H_0	141.81
Observations	778
R^2	0.96

OLS estimation. t-stat. in parenthesis

the density concentrates around a Gini coefficient of 0.300. Thus, although the distribution is clearly not normal, in 1990 the standard deviation of the Gini coefficient is well below that of any other preceding year.

This general reduction in the mean and the dispersion of the distribution of human capital shall be analysed thoroughly. In particular, we analyse the relative position of each country and its evolution over time, taking into account the concept of Quah's probability transitional matrix.[9] Instead of calculating this matrix, in Figure 3 we plot the relative position of the Gini coefficient across countries in 1960 against their relative position in 1990, dividing the sample in 1960 in five intervals. The cutting points between intervals are 1/4, 1/2, 1 and 2 times the average of the Gini coefficient in logs. The diagonal simply reflects the values of the Gini coefficient in 1960 multiplied by the sample average rate of growth between 1960 and 1990. The intersection of the vertical lines between each interval and the diagonal allows us to obtain the corresponding intervals in 1990. Thus, countries win or loose relative positions according to the vertical distance to the diagonal.

This procedure allows us to prove, first, the existence of convergence or polarisation of the Gini coefficient: if countries had converged, we should observe that countries change from their initial intervals in 1960 to the one around the average in 1990. Second, it allows us to identify in which countries inequality has improved in relative terms (those that change to groups with less inequality) and those in which it has worsened. As we can see in Figure 3, some countries that were in the fourth interval in 1960 have improved in equality, changing to the third interval in 1990. The biggest reduction in inequality takes place in Korea, Taiwan and Hong Kong. Likewise, countries that were in the third interval in 1960 have reduced inequality and have changed to the second one in 1990. This is the case of Romania, Bulgaria and Fiji. Moreover, some countries that

[9] Quah takes each country's per capita GDP relative to the world average and discretises the set of possible values into intervals at 1/4, 1/2, 1 and 2. The probality transitional matrix indicates the probability that an economy in income group i transits to income group j. See Quah (1993,1996)

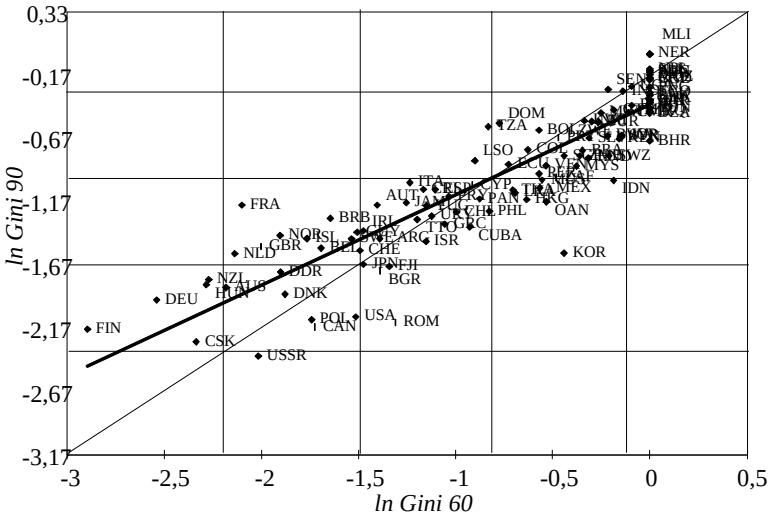

Figure 3: *Convergence of the Gini Coefficient*

showed absolute inequality in 1960 (that were in the fifth interval), have reduced inequality, changing to the fourth interval in 1990. This has happened, for example, in Bahrain, Algeria, Cameroon or Tunisia. On the contrary, the countries that have worsened their relative position are, mainly, some European countries. On the one hand, Finland, Germany, New Zealand, Hungary and Ckecolovaquia have changed from the first interval in 1960 to the second one in 1990. On the other, countries such as France, The Netherlands, Belgium, Norway or the United Kingdom have changed from the second to the third interval.

Finally, Figure 3 also shows the adjusted values of the Gini index in 1990 after estimating an equation where the Gini index in 1960 is the regressor, both in logs. The smaller the slope of the adjusted line, the bigger the convergence process is. As we can see in this figure, it seems that during the period 1960 to 1990 there has been a process of convergence since the slope of the regression line is smaller than the slope of the diagonal line (the estimated coefficient is equal to 0.714 with a t-ratio equal to 20.57).

5. Correlation between human inequality and other indicators of development

This section provides some additional empirical evidence about the relationships be-

tween human capital inequality, measure through the Gini coefficient (G^h) and other indicators of development such as the level (y) and the rate of growth ($\Delta \ln y$) of GDP per capita, the stock of human capital (H), human capital accumulation (s_h), life expectancy (LE), population growth (n), income inequality (G^y), the ratio of government expenditure on education to GDP (s_h^g), the investment rate (s_k), the ratio of government consumption to GDP (g) or income inequality (G_y).

From Table 6, which contains the correlation matrix between the variables under consideratio, we can observe the following results:

1. There is a strong negative relationship between the Gini index and the stock of human capital (H), measured as average years of schooling in the total population. This suggests that, societies with a higher stock of human capital are also the societies with the best distribution in education. Figure 4 illustrates the relationship between the stock of human capital and inequality in the distribution of human capital.[10] Countries such as the USA, Canada or New Zealand with the highest average schooling years in the total population (higher than 10 years), also have a low human capital Gini coefficient. However, though the relation between these two variables is negative, we can observe in these figure that there are a few countries that, in spite of their low Gini coefficient, they have very few years of schooling in the total population (5 or less years). This happens in the 60s in some European countries, for example, in Austria, France, the Netherlands or Norway. All these countries start with a low number of schooling years in the total population but with a very good distribution of education. Nevertheless, from the 60s to the 90s, they have increased the schooling years as well as the inequality in their distribution. Likewise Finland, with less schooling years than the USA, Canada or New Zealand, is the county with the best distribution in education.
   This negative correlation holds with the rate of human capital accumulation (s_h). Figure 5 shows that higher human capital inequality has tended to have a negative impact on human capital accumulation rates in most countries during the period 1960-1990.[11]

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[10] The results of the estimated equation in Figure 4 are as follows:

$$\begin{aligned} H_{it} &= 9.173 - 8.814 G_{it}^h \\ & \quad (85.4) \quad (-61.2) \end{aligned}$$

where $R^2 = 0.823$ and the number of observations is 778.

[11] Human capital accumulation is measured as the percentage of secondary schooling attained in the total population aged 15 and over, from Barro and Lee (1996). The results of the estimated equation in Figure 5 are as follows:

$$s_{h_{it}} = 41.338 - 39.896 G_{it}^h$$

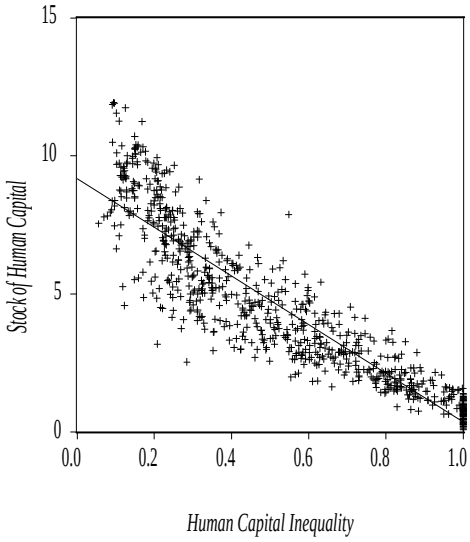

Figure 4: *Human capital inequality and the level of human capital (average years of schooling).*

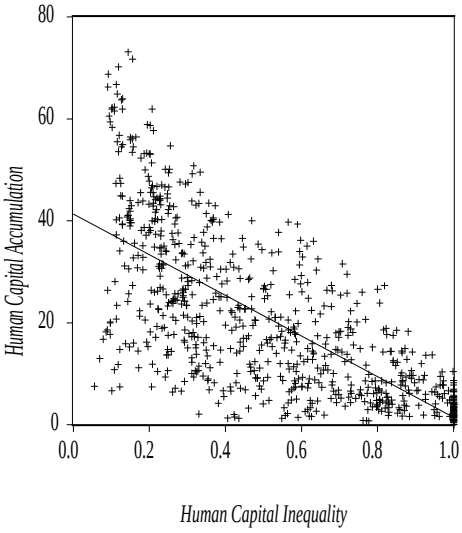

Figure 5: *Human capital inequality and human capital accumulation.*

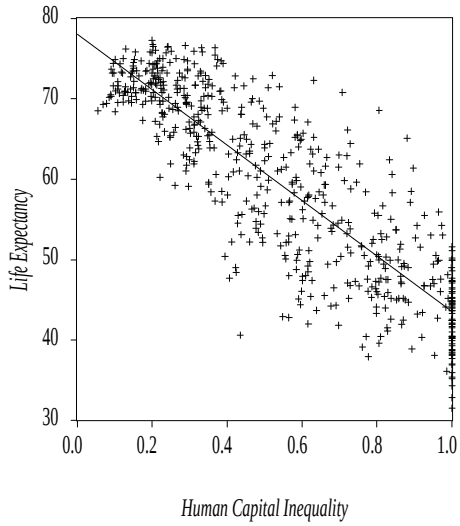

Figure 6: *Human capital inequality and life expectancy (years).*

2. Similarly, there is a strong relationship between the Gini index and the life expectancy (LE). Countries with more equalitarian distribution of human capital are the countries in which their citizens, on average, live longer. Figure 6 shows that countries with life expectancy around 70 years old coincide with the countries with the best distribution in human capital. In opposition, the countries with greater inequality have a life expectancy less than 50 years old. In particular, Mozambique and Mali are the countries with less life expectancy in 1960 (35.2 and 35.9 years respectively), and they exhibit absolute inequality in the distribution of human capital. In opposition, OECD and High Income countries have a life expectancy greater than 70 years old. The highest values are 77.3 years old in Japan, followed by 76.7 in Switzerland and 76.6 in France, all of them in 1985.[12]
3. There is a negative correlation between the Gini index and government expenditure on education (s_h^g). Although the correlation is not too big, this negative sign may

$$(39.97) \quad (-28.80)$$

where $R^2 = 0.518$ and the number of observations is 778.

[12] The results of the estimated equation in Figure 6 are as follows

$$\begin{aligned} LE_{it} &= 77.977 - 34.445\ G_{it}^h \\ & \quad (196.9) \quad (-50.22) \end{aligned}$$

where $R^2 = 0.745$ and the number of observations is 588.

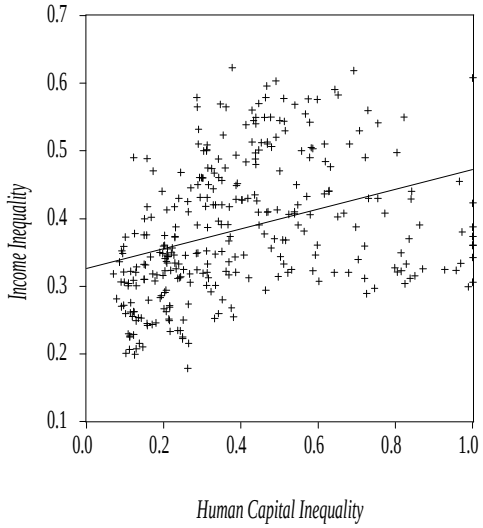

Figure 7: *Income inequality and human capital inequality*

suggest that societies with less inequality in human capital are those in which government spend more on education.

4. Countries with the highest income per capita (y) are also the countries with the best distribution in human capital. This negative correlation also applies with the rate of growth of GDP per capita ($\Delta \ln y$) and with the investment rate (s_k).
5. There is a positive correlation between human capital inequality and the population growth rate (n).
6. Income inequality (G^y) and human capital inequality are correlated positively. Nevertheless, this coefficient is not too high (0.35). As we pointed out in section two, the group of countries with the worst distribution in income (Latin America) does not coincide with the group of countries with the worst distribution in human capital (South Asia). There are only two groups of countries that are situated in the same relative positions in both distributions: OECD and Eastern European countries have the best distribution in both, income and education. The positive correlation between the income Gini and the human capital Gini coeffcients is shown in Figure 7.[13]

[13] The results of the estimated equation in Figure 7 are as follows

$$\begin{array}{rcl} G^y & = & 0.326 + 0.146 G^h_{it} \\ & & (33.50) \quad (6.11) \end{array}$$

where R^2=0.120 and the number of observations is 313.

Table 6
Correlation Matrix of different indicators of development

	G^h	H	s_h	LE	y	$\Delta \ln y$	n	$\Delta \ln G^h$	s_h^g	g	s_k	G^y
G^h	1.00											
H	-0.91	1.00										
	(778)											
s_h	-0.72	0.89	1.00									
	(778)	(778)										
LE	-0.86	0.85	0.76	1.00								
	(588)	(588)	(602)									
y	-0.68	0.80	0.75	0.76	1.00							
	(677)	(677)	(689)	(597)								
$\Delta \ln y$	-0.15	0.13	0.10	0.18	0.03	1.00						
	(571)	(571)	(583)	(579)	(597)							
n	0.54	-0.53	-0.42	-0.39	-0.61	-0.15	1.00					
	(502)	(502)	(514)	(508)	(511)	(511)						
$\Delta \ln G^h$	-0.22	0.15	0.08	0.13	0.17	-0.01	-0.20	1.00				
	(662)	(662)	(662)	(587)	(593)	(571)	(501)					
s_h^g	-0.37	0.47	0.46	0.39	0.47	-0.06	-0.27	0.02	1.00			
	(458)	(458)	(465)	(464)	(467)	(467)	(478)	(457)				
g	0.42	-0.36	-0.27	-0.41	-0.37	-0.20	0.24	-0.08	0.18	1.00		
	(595)	(595)	(608)	(602)	(620)	(597)	(514)	(595)	(469)			
s_k	-0.66	0.64	0.52	0.69	0.57	0.30	-0.46	0.12	0.35	-0.37	1.00	
	(595)	(595)	(608)	(602)	(620)	(597)	(514)	(595)	(469)	(625)		
G^y	0.35	-0.48	-0.36	-0.30	-0.40	-0.07	0.53	-0.05	-0.25	-0.01	-0.34	1.00
	(313)	(313)	(313)	(238)	(287)	(230)	(180)	(250)	(172)	(235)	(235)	

The number of observations is in brackets.

To sum up, we have seen that human capital inequality and the stock of human capital are strongly and negatively correlated and that the stock of human capital is negatively correlated with income inequality. Moreover, the countries with more expenditure in education are also the countries with less inequality in human capital. Thus, these correlations suggest that universal education could reduce human capital inequality and increase the stock of education, which could translate into a reduction in income inequality. Nevertheless, more evidence on these relations is needed.

6. Human Capital Inequality and Economic Growth

Once we have calculated the correlations between human capital inequality and other indicators of development, in this section we focus on the effect that human capital inequality can exert on economic growth rates. To consider this issue we add inequality variables to an equation where the average economic growth is explained by initial per capita income and the average accumulation rates of human and physical capital. Next,

we increase the set of explanatory variables to prove the robustness of the initial results. Finally, we repeat the exercises with different samples.

The data used in the following regressions comes from Barro and Lee (1994, 1996) with the exception of the variables concerning inequality. With regard to these variables we use the following data. First, income inequality (G^y) is proxied by Deininger and Squire's (1996) high quality income Gini coefficient. Although we would like to include this variable at the beginning of the period (next to 1960), the problems with the availability of high quality income Gini data restrict us to including this variable as an average.[14] Second, human capital inequality (G^h) is measured as the initial human capital Gini coefficient constructed as described in Section 2.

In the initial regression, presented in Column 1 of Table 7, the average growth rate ($\Delta \ln y$) is the dependent variable and income inequality is included as an explicative variable along with the logs of human capital accumulation ($\ln\ s_h$), physical capital accumulation ($\ln\ s_k$) and initial per capita income ($\ln\ y$). The results are as expected, on the one hand, the coefficients of the accumulation of factors are positive and statistically significant and, on the other, initial income per capita and income inequality coefficients are negatively and significantly related to per capita income growth.[15] Nevertheless, these results are not robust when we add other variables as regressors. Firstly, initial human capital inequality, measured through the Gini coefficient in 1960, is added to this previous set of regressors. Column 2 indicates that whereas the coefficient of human capital inequality is not statistically significant, its inclusion reduces the significance of the coefficients of the variables included as regressors.[16] However, the main changes take place once regional dummies are included as regressors. We include these variables to collect permanent and specific characteristics of the regions that otherwise could bias the coefficients of some explanatory variables. Column 3 adds regional dummies along with other variables related to growth, the black market premium (BMP) and the ratio

[14] The inclusion of the income Gini at the beginnig of the period reduces significantly the size of the sample. As the variability of this coefficient is very low during the whole period (see Li, Squire and Zou (1998)) the inclusion of this variable as an average does not change the main results. Results with initial income Gini are not shown in the following regression but are available upon request.

[15] A negative (positive) relationship between income inequality (equality) and growth can be found in Alesina and Rodrik (1994), Persson and Tabellini (1994), Clarke (1995) or Perotti (1996), among others.

[16] Birdsall and Londoño (1997) obtain a negative and statistically significant coefficient of educational inequality in their growth equation. Nevertheless, they use the standard deviation of years of education of adults aged 25 years and over as the measure of the distribution of education. In our opinion, this measure has a disadvantage since this variable does not control for the effect of any changes in the average level of education on the distribution.

of government consumption to GDP (g), to the equation estimated in the second column. On the one hand, the results show that the coefficient of human capital accumulation is not statistically significant. On the other, the coefficient of income inequality not only stops being significant but also changes its sign. In opposition, although the initial human capital Gini coefficient is not statistically significative, its coefficient becomes negative and its t-statistic increases. In Column 4 the income Gini coefficient is excluded from the set of regressors. As a result, the significance of variables increases as well as the adjusted R^2.

These initial results suggest that the negative relation between income inequality and growth, obtained in previous studies, is not robust to the inclusion of other variables in the regression. In particular, the results may indicate that this variable is collecting specific characteristics of regions since once regional dummies are taken into account, income inequality stops being significant.[17]

Nevertheless, Table 7 is considering only a direct effect from inequality to growth but it is also possible that inequality variables are related indirectly to economic growth through the accumulation of factors. Columns 5 and 6 show that once the rates of human and physical capital accumulations are ruled out from the set of explanatory variables, initial human capital inequality has a negative and significant effect on the economic growth rates. Thus, to analyse an indirect effect from initial inequality to economic growth we should investigate if human capital inequality is associated with lower accumulation rates of human and physical capital. Table 8 presents the results when physical and human capital accumulation are included in the model as dependent variables. Column 1 shows that human capital inequality has a significant and negative effect on physical capital accumulation. Moreover, this result holds with the inclusion of additional variables such as regional dummies (column 2) and black market premium and public consumption in Column 3. Thus, this negative effect from initial human capital inequality to physical capital accumulation seems to be robust to the inclusion of different explanatory variables in the equation.

In opposition, the results concerning income inequality are quite different since the effect of the income Gini coefficient on physical capital accumulation seems to be positive once regional dummies are taken into account. When we exclude this variable from the set of regressors the significance of all coefficients increases (Column 4). In the remaining columns (5-8), human capital accumulation is the dependent variable. In these regressions initial human capital inequality seems to have a significant and negative effect on human capital accumulation once regional dummies are included as regressors. However, when we introduce life expectancy (LE) the coefficient of human

[17] A similar result is obtained by Deininger and Squire (1998).

capital inequality stops being significant (Column 8).[18] In addition, the effect of income inequality on human capital accumulation is null. Column 7 shows that the exclusion of this variable increases the significance of the human capital inequality coefficient. Finally, Columns 6, 7 and 8 also show that public spending in education (s_h^g) has exerted a positive effect on the rates of human capital accumulation.

As the human capital Gini coefficient is available for 116 countries from 1960 to 1990, we can test if the previous results hold with pool data. However, when the data are extended in its temporal dimension one question emerges. As income Gini coefficients are not available for all countries in five year intervals from 1960 to 1990 we have to rule income inequality out from the set of explicative variables. The results of these estimations are displayed in Table 9. Column 1 presents the basic economic growth regression increased by the human capital Gini coefficient and regional dummies. The results show that, whereas human capital inequality coefficient is negative and statistically significant at a 10% level, human capital accumulation has no effect on economic growth and, moreover, its coefficient is negative.[19] The coefficients of the three regional dummies are statistically significant.

With regard to the effect of human capital inequality in the accumulation of factors, Columns 2 to 5 confirm the results obtained in Table 8. On the one hand, the negative and significant effect of initial human capital inequality on the accumulation of physical capital seems to be robust to the inclusion of different regressors. On the other, the negative relation of initial human capital inequality and human capital accumulation does not hold when life expectancy or infant mortality are included in the equation.

Since these results suggest that human capital inequality may affect economic growth through its effect on the accumulation of factors, in the last two columns we exclude factors accumulation from the economic growth equation. The results show that human capital inequality has a negative and significant effect on economic growth rates.

A summary of the results is as follow. First, the negative effect of income inequality on economic growth rates is not robust to the inclusion of different regressors. In particular, this variable is no longer significant when regional dummies are added to the set of regressors. Second, part of the negative effect of initial human capital inequality upon economic growth is given by the negative correlation of human inequality with the accumulation of human and physical capital. With regard to the negative effect of initial human capital inequality on physical capital accumulation, the results seems to be

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[18] After trying different combinations of the regressors, we have noticed that human capital inequality is very sensitive to the inclusion of life expectancy or infant mortality.

[19] Islam (1995) also obtains negative coefficients when, instead of the percentage of secondary schooling attained in the total population, he uses average schooling years in the total population.

Table 7
Dependent variable: Average growth rate 1960-1990

	(1)	(2)	(3)	(4)	(5)	(6)
C	0.131	0.127	0.131	0.144	0.065	0.111
	(5.15)	(4.38)	(5.03)	(6.65)	(2.70)	(4.79)
$\ln y$	-0.011	-0.011	-0.012	-0.012	-0.005	-0.011
	(-3.64)	(-3.09)	(-3.87)	(-5.13)	(-1.67)	(-4.11)
$\ln s_h$	0.008	0.009	0.004	0.004		
	(3.18)	(2.71)	(1.64)	(2.17)		
$\ln s_k$	0.019	0.019	0.014	0.015		
	(4.37)	(3.44)	(1.91)	(3.54)		
G^y	-0.039	-0.037	0.022		0.027	0.029
	(-2.55)	(-2.15)	(0.95)		(1.08)	(1.15)
G^h		0.002	-0.012	-0.011	-0.019	-0.022
		(0.17)	(-1.17)	(-1.54)	(-2.33)	(-2.74)
BMP			-0.005	-0.005		-0.010
			(-1.67)	(-2.32)		(-1.34)
g			-0.017	-0.021		-0.039
			(-0.53)	(-0.83)		(-1.23)
s_h^g						0.246
						(1.72)
Laam			-0.016	-0.014	-0.018	-0.019
			(-3.21)	(-5.23)	(-3.82)	(-3.90)
Safrica			-0.020	-0.018	-0.020	-0.026
			(-2.87)	(-4.12)	(-3.26)	(-4.27)
Asiae			0.012	0.012	0.015	0.015
			(1.68)	(1.91)	(2.03)	(1.83)
R^2 *adj*	0.360	0.342	0.580	0.657	0.413	0.531
Nob	74	72	67	83	72	65

Note: Cross-country regressions. OLS estimation. Dependent variable: Δlny. The t-statistics use the White adjustment for heteroskedasticity.

robust to the inclusion of different regressors. Third, these results for the overall sample hold with cross-country and pool estimations and are also supported when we do the same regressions for developing countries separately.[20]

[20] The results of developing countries are available upon request.

Table 8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln s_k$	$\ln s_k$	$\ln s_k$	$\ln s_k$	$\ln s_h$	$\ln s_h$	$\ln s_h$	$\ln s_h$
C	-1.803	-1.875	-1.486	-1.008	-0.550	-0.039	0.392	-0.862
	(-3.12)	(-2.81)	(-1.77)	(-1.30)	(-0.36)	(-0.04)	(0.41)	(-0.76)
$\ln y$	0.007	0.002	-0.010	-0.103	0.524	0.381	0.340	0.231
	(0.09)	(0.02)	(-0.10)	(-1.02)	(3.38)	(3.37)	(3.14)	(2.17)
$\ln s_h$	0.183	0.107	0.123	0.291				
	(2.64)	(1.52)	(1.66)	(2.26)				
G^y	-0.240	1.068	0.680		-0.606	-0.389		
	(-0.47)	(1.99)	(1.09)		(-0.77)	(-0.34)		
G^h	-0.654	-0.763	-0.793	-0.770	-0.603	-0.606	-0.825	-0.112
	(-2.81)	(-3.67)	(-3.10)	(-3.26)	(-1.64)	(-2.05)	(-3.18)	(-0.26)
BMP			0.027	-0.146				
			(0.16)	(-0.74)				
g			-1.437	-1.608				
			(-1.61)	(-1.90)				
s_h^g						15.371	11.344	10.793
						(3.08)	(2.34)	(2.37)
LE								0.029
								(2.08)
Laam		-0.363	-0.278	-0.229		0.100	-0.003	0.065
		(-3.01)	(-2.14)	(-2.33)		(0.47)	(-0.03)	(0.56)
Safrica		-0.377	-0.238	-0.041		-0.201	-0.244	--0.107
		(-2.26)	(-1.10)	(-0.21)		(-0.71)	(-1.37)	(-0.57)
Asiae		0.012	0.057	0.028		0.500	0.374	0.362
		(0.08)	(0.37)	(0.22)		(2.79)	(2.14)	(2.55)
R^2 *adj*	0.454	0.511	0.564	0.584	0.575	0.676	0.688	0.706
Nob	72	72	67	83	72	70	85	83

Note: Cross-country regressions. OLS estimation. Dependent variables are physical capital accumulation (Columns 1 to 4) and human capital accumulation (Columns 5 to 8). The t-statistics use the White adjustment for heteroskedasticity.

Table 9

	(1) $\Delta \ln y$	(2) $\ln s_k$	(3) $\ln s_k$	(4) $\ln s_h$	(5) $\ln s_h$	(6) $\Delta \ln y$	(7) $\Delta \ln y$
C	0.113	-2.244	-0.810	-0.387	0.297	0.111	0.178
	(3.77)	(-7.11)	(-1.59)	(-0.80)	(0.26)	(4.47)	(5.40)
$\ln y$	-0.007	0.137	-0.022	0.471	0.242	-0.009	-0.015
	(-2.31)	(4.09)	(-0.38)	(9.35)	(3.02)	(-3.34)	(-4.41)
$\ln s_h$	-0.002	-0.001	0.079				
	(-1.09)	(-0.04)	(1.65)				
$\ln s_k$	0.007						
	(1.96)						
G^h	-0.021	-1.053	-0.972	-1.347	-0.398	-0.028	-0.026
	(-1.74)	(-8.67)	(-6.11)	(-8.56)	(-1.51)	(-3.26)	(-2.49)
BMP			-0.157				-0.010
			(-2.17)				(-3.58)
g			-1.854				-0.103
			(-3.92)				(-3.28)
s_h^g					13.716		
					(4.99)		
LE					0.006		
					(0.41)		
Inf. Mort					-4.968		
					(-1.90)		
Laam	-0.016	-0.215	-0.313	0.023	0.165	-0.018	-0.024
	(-4.24)	(-4.63)	(-6.01)	(0.37)	(1.90)	(-5.44)	(-6.31)
Safrica	-0.019	-0.194	-0.245	-0.177	-0.295	-0.021	-0.025
	(-3.79)	(-2.33)	(-2.76)	(-1.82)	(-1.85)	(-4.86)	(-5.07)
Asiae	0.015	0.140	-0.029	0.293	0.389	0.011	0.010
	(2.82)	(2.58)	(-0.38)	(3.97)	(3.26)	(2.28)	(1.77)
R^2 *adj*	0.161	0.493	0.504	0.636	0.690	0.125	0.266
Nob	477	592	451	676	343	571	433

Note: Pooled regressions. 2SLS estimation, instrumens are explanatory variables lagged one period. Dependent variables are: Dlny in columns 1, 6 and 7, physical capital accumulation in columns 2 and 3 and human capital accumulation in columns 4 and 5. The t-statistics use the White adjustment for heteroskedasticity.

7. Conclusions

Much of the empirical literature that has analysed the relationship between inequality and growth has focused on income inequality as a proxy for wealth inequality. The main reason for using income inequality instead of wealth inequality or assets inequality in this relationship is because, in spite of its shortcomings, income inequality data are available for a sufficient number of countries and periods. Some exceptions are the studies in which the distribution of wealth has been proxied by the distribution of assets, for example, land distribution. Nevertheless, income or land inequality can be insufficient measures of wealth inequality since other assets such as human capital are important determinants of development. The main objective of this paper is to provide indicators of human capital inequality for a large sample of countries and years and to analyse their influence on the economic growth process.

To construct the indicators of human capital inequality we have distributed school attainment levels by quintiles and we have calculated a human capital Gini coefficient. The main advantage of this indicator is that it complements conveniently the information provided by income inequality measures. Moreover, because human capital inequality measures are constructed from Barro and Lee's (1996) date set, these measures are available for 116 countries from 1960 to 1990, so there is a total of 778 observations.

Using this new indicator the main findings are the following. First, the variability of the human capital Gini coefficient is greater across countries than within each country. Nevertheless, as a result of a general reduction of this index with the exception of OECD countries, a process of convergence in Gini coefficients has taken place. Second, there is a strong negative relationship between the Gini index and the stock of human capital. This negative correlation holds with the rate of human capital accumulation as well. Third, there is a strong correlation between the Gini index and life expectancy. Fourth, income inequality and human capital inequality are correlated positively but this coefficient is not too high. Fifth, with cross-country and pool data we obtain a negative effect of human capital inequality on economic growth. Mainly, this effect is conducted through the negative and robust relation between initial human capital inequality and the accumulation of factors.

In total, these findings reveal that human capital inequality seems to be an important determinant of development. A more equalitarian distribution of education is not only associated with a high stock of human capital or a better life expectancy but also with higher accumulation of physical and human capital and higher growth rates in per capita income.

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9. Appendix

Human capital Gini coefficient for 116 countries

	Obs.	Cov	Mean	St. Dv	Max	Min	G^h_{60}	G^h_{90}	H
S.Sah.Africa	166	60-90	0.774	0.182	1.000	0.341	0.832	0.694	2.134
BEN	5	70-90	0.966	0.052	1.000	0.881		0.882	1.088
BWA	7	60-90	0.694	0.121	0.810	0.522	0.803	0.522	2.519
CMR	7	60-90	0.700	0.099	0.893	0.630	0.893	0.630	2.253
CAF	7	60-90	0.945	0.075	1.000	0.822	1.000	0.822	1.090
COG	2	85-90	0.607	0.012	0.615	0.598		0.598	5.015
GMB	4	75-90	0.981	0.039	1.000	0.923		0.923	1.160
GHA	7	60-90	0.820	0.111	0.990	0.703	0.990	0.703	2.756
GNB	3	80-90	0.983	0.029	1.000	0.949		0.949	0.467
KEN	7	60-90	0.709	0.143	0.853	0.511	0.852	0.511	2.580
LSO	7	60-90	0.417	0.013	0.430	0.394	0.410	0.430	3.260
LBR	7	60-90	0.945	0.072	1.000	0.847	1.000	0.847	1.450
MWI	7	60-90	0.688	0.077	0.777	0.617	0.777	0.628	2.349
MLI	7	60-90	1.000	0.000	1.000	1.000	1.000	1.000	0.600
MUS	7	60-90	0.433	0.091	0.574	0.341	0.574	0.369	4.467
MOZ	7	60-90	0.934	0.073	1.000	0.828	1.000	0.828	0.680
NER	7	60-90	1.000	0.000	1.000	1.000	1.000	1.000	0.479
RWA	5	70-90	0.837	0.109	1.000	0.715		0.715	1.444
SEN	7	60-90	0.769	0.058	0.838	0.678	0.806	0.755	1.986
SLE	7	60-90	0.962	0.049	1.000	0.874	1.000	0.874	1.340
ZAF	7	60-90	0.526	0.113	0.618	0.351	0.612	0.377	4.489
SDN	7	60-90	0.951	0.059	1.000	0.865	1.000	0.870	0.884
SWZ	7	60-90	0.635	0.155	0.810	0.447	0.810	0.447	3.277
TZA	7	60-90	0.563	0.064	0.627	0.435	0.435	0.563	2.720
TGO	7	60-90	0.907	0.110	1.000	0.736	1.000	0.736	1.518
UGA	7	60-90	0.819	0.050	0.908	0.773	0.908	0.773	1.420
ZAR	7	60-90	0.825	0.110	1.000	0.691	1.000	0.691	1.690
ZMB	7	60-90	0.598	0.102	0.698	0.447	0.698	0.446	3.576
ZWE	7		0.587	0.041	0.660	0.540	0.660	0.540	2.256
Reunion	5	60-90	0.584	0.084	0.730	0.520	0.730		3.074
M. East & N. Africa	69	60-90	0.775	0.177	1.000	0.205	0.875	0.601	3.045
DZA	7	60-90	0.834	0.145	1.000	0.627	1.000	0.627	2.151
EGY	4	75-90	0.821	0.134	0.973	0.679		0.680	2.935
TUN	7	60-90	0.840	0.136	1.000	0.650	1.000	0.650	2.217
BHR	7	60-90	0.764	0.180	1.000	0.502	1.000	0.502	2.931
IRN	7	60-90	0.878	0.123	1.000	0.679	1.000	0.679	2.282
IRQ	7	60-90	0.863	0.148	1.000	0.637	1.000	0.636	2.074
ISR	7	60-90	0.257	0.050	0.335	0.205	0.315	0.227	8.489
JOR	7	60-90	0.695	0.120	0.865	0.525	0.865	0.525	3.936
KWT	7	60-90	0.699	0.070	0.806	0.590	0.714	0.590	3.993
SYR	7	60-90	0.712	0.126	0.857	0.520	0.857	0.520	3.039
ARE	1	75	0.880	-	0.880	0.880			2.870
YEM	6	75-90	0.993	0.015	1.000	0.970		0.970	0.688
LBY	6	60-85	0.841	0.123	1.000	0.690	1.000		1.985
South Asia	42	60-90	0.846	0.220	1.000	0.330	0.895	0.750	2.162
AFG	7	60-90	1.000	0.000	1.000	1.000	1.000	1.000	1.241
BGD	7	60-90	0.926	0.085	1.000	0.815	1.000	0.815	1.391
IND	7	60-90	0.821	0.040	0.870	0.746	0.870	0.746	2.804
NPL	7	60-90	0.979	0.043	1.000	0.885	1.000	0.885	0.667
PAK	7	60-90	0.934	0.099	1.000	0.719	1.000	0.720	1.891
LKA	7	60-90	0.416	0.076	0.500	0.330	0.500	0.334	4.976

Human capital Gini coefficient for 116 countries (cont.)

	Obs.	Cov	Mean	St. Dv.	Max	Min	G^h_{60}	G^h_{90}	H
East Asia & Pacific	84	60-90	0.484	0.198	1.000	0.187	0.604	0.378	5.052
BUR	7	60-90	0.821	0.096	0.909	0.665	0.909	0.665	1.653
CHN	7	75-90	0.505	0.075	0.595	0.407		0.407	4.980
HKG	7	60-90	0.424	0.084	0.530	0.316	0.530	0.316	7.090
IDN	7	60-90	0.579	0.184	0.828	0.368	0.828	0.368	3.070
JPN	7	60-90	0.206	0.013	0.229	0.189	0.229	0.189	8.120
KOR	7	60-90	0.399	0.157	0.642	0.207	0.642	0.207	6.811
MYS	7	60-90	0.528	0.099	0.684	0.412	0.684	0.412	4.473
PHL	7	60-90	0.346	0.069	0.438	0.288	0.438	0.288	5.651
SGP	7	60-90	0.532	0.072	0.644	0.447	0.644	0.447	5.306
OAN	7	60-90	0.427	0.107	0.587	0.310	0.587	0.311	6.201
THA	7	60-90	0.377	0.062	0.494	0.312	0.494	0.342	4.493
FJI	7	60-90	0.250	0.049	0.322	0.187	0.261	0.187	6.261
PNG	7	60-90	0.894	0.091	1.000	0.768	1.000	0.768	1.561
Latin America	168	60-90	0.447	0.175	1.000	0.145	0.497	0.401	4.491
BRB	7	60-90	0.221	0.056	0.276	0.145	0.193	0.273	7.506
CRI	7	60-90	0.321	0.013	0.343	0.304	0.312	0.343	4.771
DOM	7	60-90	0.535	0.047	0.582	0.461	0.460	0.579	3.493
SLV	7	60-90	0.590	0.109	0.731	0.451	0.731	0.514	2.839
GTM	7	60-90	0.746	0.090	0.830	0.643	0.830	0.643	2.177
HTI	7	60-90	0.881	0.141	1.000	0.678	1.000	0.696	1.680
HND	7	60-90	0.592	0.110	0.729	0.438	0.729	0.438	2.844
JAM	7	60-90	0.285	0.044	0.353	0.208	0.285	0.309	3.667
MEX	7	60-90	0.478	0.078	0.574	0.347	0.567	0.347	4.280
NIC	7	60-90	0.662	0.052	0.742	0.587	0.742	0.587	2.999
PAN	7	60-90	0.395	0.050	0.446	0.318	0.417	0.318	5.717
TTO	7	60-90	0.281	0.030	0.318	0.228	0.301	0.270	5.949
ARG	7	60-90	0.237	0.014	0.257	0.220	0.249	0.232	6.494
BOL	7	60-90	0.580	0.021	0.602	0.547	0.565	0.548	5.293
BRA	7	60-90	0.562	0.094	0.706	0.467	0.706	0.466	3.214
CHL	7	60-90	0.312	0.033	0.368	0.286	0.368	0.287	5.883
COL	7	60-90	0.471	0.033	0.533	0.433	0.533	0.468	4.324
ECU	7	60-90	0.449	0.036	0.485	0.403	0.483	0.418	4.649
GUY	7	60-90	0.232	0.016	0.250	0.213	0.221	0.244	4.948
PRY	7	60-90	0.326	0.021	0.355	0.300	0.355	0.324	4.416
PER	7	60-90	0.471	0.081	0.588	0.388	0.565	0.388	4.881
URY	7	60-90	0.302	0.027	0.340	0.267	0.325	0.277	6.071
VEN	7	60-90	0.511	0.110	0.632	0.387	0.586	0.413	4.126
Cuba	7	60-90	0.287	0.082	0.415	0.207	0.400	0.254	5.573
Eastern Europe	56	60-90	0.182	0.072	0.359	0.092	0.186	0.157	7.971
HUN	7	60-90	0.134	0.023	0.161	0.102	0.102	0.161	8.116
POL	7	60-90	0.150	0.021	0.175	0.123	0.175	0.123	8.169
YUG	7	60-90	0.311	0.031	0.359	0.268	0.316	0.302	5.949
BGR	7	60-90	0.242	0.029	0.265	0.180	0.247	0.180	7.214
CSK	7	60-90	0.113	0.012	0.129	0.097	0.097	0.103	8.711
DDR	7	60-90	0.151	0.014	0.178	0.130	0.149	0.178	9.161
ROM	7	60-90	0.237	0.052	0.269	0.120	0.269	0.120	7.279
USSR	7	60-90	0.120	0.014	0.133	0.092	0.133	0.091	9.173

Human capital Gini coefficient for 116 countries (cont.)

	Obs.	Cov	Mean	St. Dv.	Max	Min	G^h_{60}	G^h_{90}	H
OECD & High Income	161	60-90	0.251	0.139	0.766	0.055	0.237	0.252	7.395
CAN	7	60-90	0.169	0.034	0.204	0.116	0.178	0.116	9.977
USA	7	60-90	0.166	0.057	0.220	0.091	0.220	0.125	10.284
AUT	7	60-90	0.299	0.033	0.342	0.245	0.245	0.302	5.849
BEL	7	60-90	0.195	0.013	0.215	0.183	0.184	0.215	8.374
CYP	7	60-90	0.387	0.021	0.422	0.356	0.400	0.356	5.959
DNK	7	60-90	0.149	0.004	0.153	0.143	0.153	0.150	10.201
FIN	7	60-90	0.098	0.027	0.123	0.055	0.055	0.114	8.704
FRA	7	60-90	0.229	0.068	0.302	0.123	0.122	0.302	5.561
DEU	7	60-90	0.101	0.022	0.143	0.079	0.079	0.143	8.239
GRC	7	60-90	0.325	0.033	0.350	0.261	0.347	0.261	6.229
ISL	7	60-90	0.212	0.024	0.233	0.171	0.171	0.232	6.961
IRL	7	60-90	0.230	0.008	0.247	0.221	0.229	0.247	7.153
ITA	7	60-90	0.321	0.048	0.385	0.264	0.290	0.362	5.631
NLD	7	60-90	0.181	0.032	0.206	0.118	0.118	0.206	7.441
NOR	7	60-90	0.214	0.033	0.243	0.149	0.149	0.238	6.773
PRT	7	60-90	0.560	0.044	0.623	0.510	0.623	0.516	3.079
ESP	7	60-90	0.337	0.037	0.381	0.269	0.331	0.342	5.291
SWE	7	60-90	0.240	0.016	0.264	0.215	0.215	0.232	8.807
CHE	7	60-90	0.232	0.037	0.294	0.195	0.225	0.211	7.924
TUR	7	60-90	0.669	0.063	0.766	0.582	0.766	0.582	2.826
GBR	7	60-90	0.198	0.033	0.219	0.135	0.135	0.219	8.064
AUS	7	60-90	0.146	0.019	0.166	0.113	0.113	0.158	9.977
NZL	7	60-90	0.115	0.026	0.168	0.034	0.103	0.168	10.790
TOTAL	778	60-90	0.521	0.289	1.000	0.055	0.562	0.461	4.498