

Human Capital Inequality and Economic Growth: Some New Evidence*

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July, 2001.

Abstract

This paper provides new measures of human capital inequality for a broad panel of countries. Taking attainment levels from Barro and Lee (2001), we compute Gini coefficients and the distribution of education by quintiles for 108 countries over five-year intervals from 1960 to 2000. Using this new cross-country data on human capital inequality two main conclusions are obtained. First, most countries in the world have tended to reduce the inequality in human capital distribution. Second, human capital inequality measures provide more robust results than income inequality measures in the estimation of standard growth and investment equations.

JEL classification: O15, O40

Keywords: Human capital inequality; Economic growth.

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 as, for example, in the influential work of Kuznets (1955), who analyzed the effects of economic development upon the evolution of the distribution of income. In contrast, more recent literature addresses the question of how income or wealth distribution affects the growth of income, that is, it focuses on the potential effects of inequality on economic growth through different channels.¹

* The authors wish to thank the editor, two anonymous referees, J. E. Boscá, D. Checchi, M. R. Sanmartín and participants at the XV Annual Congress of the European Economic Association and at the 2001 Annual Conference of the Royal Economic Society for very helpful comments. R. Doménech acknowledges the financial support of CICYT SEC99-0820. *Correspondence:* acastell@eco.uji.es. The data set is available at http://iei.uv.es/~rdomenec/human/h_ineq.html

¹ We can distinguish three different mechanisms in this literature: the effects of wealth 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). Excellent surveys of these theories are found in Perotti (1996) and Aghion, Caroli and García-Peñalosa (1999).

In spite of the distribution of wealth being the relevant inequality source in theoretical models, the scarcity of available data on the distribution of wealth for a broad number of countries and for sufficiently long periods leads most empirical studies to use income inequality data as a proxy for wealth inequality.² On other occasions, the distribution of wealth is proxied by the distribution of land. For example, Alesina and Rodrik (1994) and Deininger and Squire (1998) include land inequality along with income inequality to analyze the relationship between initial inequality in the asset distribution and long-term growth.

However, income and land inequality may be insufficient measures of wealth inequality since other variables such as human capital are also important determinants of wealth and growth. Thus, in some models that analyze the relationship between inequality and economic growth, the role played by human capital endowment is very important if not crucial, since the distribution of income is mainly given by the distribution of human capital. For instance, Glomm and Ravikumar (1992), Saint-Paul and Verdier (1993) or Galor and Tsiddon (1997), among others, present models in which the source of inequality is mainly determined by the distribution of human capital. But, at the same time, inequality affects human capital accumulation. In fact, some of the more interesting theories of how inequality affects growth (e.g., Galor and Zeira, 1993) are based on the interaction between imperfect credit markets, asset inequality and human capital accumulation.

The interest in these mechanisms at the theoretical level contrasts with the scarcity of empirical results. Due to the lack of available data on human capital inequality, little attention has been devoted to the influence of human capital distribution on economic growth in empirical studies. Some exceptions are Birdsall and Londoño (1997), and López, Thomas and Wang (1998). This first study analyzes a sample of 43 countries and uses the standard deviation of years of education as the measure of human capital inequality. The problem with the standard deviation, however, is that it is an absolute measure of dispersion thus it does not control for differences in the mean of the distribution. The second study uses a wider range of human capital inequality indicators but focuses on a reduced number of 12 Asian and Latin American countries.

The objective of this paper is to provide new human capital inequality measures, that allow us to make a first approximation of the relationship between these indicators and economic growth in a broad number of countries. In particular, using the recent information contained in Barro and Lee's (2001) data set about educational attainments, we calculate a human capital Gini coefficient. Additionally, to improve the information

² Measures of income inequality in growth regressions have been used by Persson and Tabellini (1994), Clarke (1995), Perotti (1996), Barro (2000) or Forbes (2000).

provided by this aggregate measure of inequality, we also compute the distribution of education by quintiles, in line with a number of contributions to the analysis of the relationship between the distribution of income and economic growth.³

Apart from their intrinsic interest, an additional advantage of our indicators is that they conveniently complement the information provided by income inequality measures. Clearly, income distribution data suffer from several problems. Besides the limitations related to their quality, the main problem arises with the different definitions of income used to measure inequality. 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, there is room for improvement in other inequality indicators, especially in developing countries where income inequality data are more scarce.

Our new measures of human capital inequality allow us to have a closer look at the relationship between inequality and economic growth. The main findings illustrate that human capital inequality measures provide more robust results than income inequality measures in the growth regressions. Moreover, the results suggest that human capital inequality negatively influences economic growth rates not only through the efficiency of resource allocation but also through a reduction in investment rates.

The structure of this paper is as follows. Section 1 presents the procedure used to obtain the Gini index and the distribution of education by quintiles, and it compares the information provided by these different measures. Section 2 analyzes the distribution of the human capital inequality indicators across countries and their evolution from 1960 to 2000. Section 3 studies the relationship between human capital inequality and economic growth. Finally, Section 4 contains the conclusions reached.

1. Measuring Human Capital Inequality

This section describes how we have obtained the measures of human capital inequality for a broad cross section of countries. We take schooling figures from Barro and Lee (2001) to construct a standard representation of inequality such as the Gini coefficient. The choice of this index to analyze 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 pointed out by Deininger and Squire (1996) among others, it is difficult to characterize inequality by such a simple measure. For this reason, to extend the information provided by the Gini index we also report figures of the distribution of education by quintiles.

³ 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.

There are different ways of computing the Gini coefficient. Since the Barro and Lee's data set provides information of the average schooling years and attainment levels, the human capital Gini coefficient (G^h) can be computed as follows:⁴

$$G^h = \frac{1}{2\bar{H}} \sum_{i=0}^3 \sum_{j=0}^3 |\hat{x}_i - \hat{x}_j| n_i n_j \quad (1)$$

where \bar{H} are the average schooling years of the population aged 15 years and over, i and j stand for the different levels of education, n_i and n_j are the shares of population with a given level of education, and \hat{x}_i and \hat{x}_j are the cumulative average schooling years of each educational level. Following Barro and Lee (2001), we consider four levels of education: no schooling (0), primary (1), secondary (2) and higher education (3). Defining x_i as the average schooling years of each educational level i , we observe that⁵

$$\hat{x}_0 \equiv x_0 = 0, \quad \hat{x}_1 \equiv x_1, \quad \hat{x}_2 \equiv x_1 + x_2, \quad \hat{x}_3 \equiv x_1 + x_2 + x_3 \quad (2)$$

Expanding expression (1) and using (2), the Gini coefficient can be computed as follows:

$$G^h = n_0 + \frac{n_1 x_2 (n_2 + n_3) + n_3 x_3 (n_1 + n_2)}{n_1 x_1 + n_2 (x_1 + x_2) + n_3 (x_1 + x_2 + x_3)} \quad (3)$$

Besides the Gini coefficient, Barro and Lee's data set can also be used to obtain the distribution of education by quintiles. Table 1 shows two examples that illustrate how these measures have been obtained for two countries which are at opposite extremes of the distribution. A good example of a large concentration of education, with a Gini coefficient close to one, is Yemen in 1975. In this country 98.8% of the population had no schooling. This means that, in terms of quintiles, the first four quintiles have no education, and all education is concentrated in the top quintile. On the contrary, a Gini coefficient close to zero would represent the case where the attainment level in each quintile is similar. A good example is the United States in 1980 where the share of total education attained by each quintile is around 0.2.

⁴ This expression has also been used in two recent papers by Thomas, Wang and Fan (2000) and Checchi (2000) to obtain a human capital Gini coefficient. In contrast with our approach, Checchi (2000) uses the information of the education for the population aged 25 years and over. For many developing countries a large portion of the labor force is younger than 25. Since most of our sample is composed of developing countries, we have used the educational information for the population aged 15 and over.

⁵ In terms of the variables of Barro and Lee's data set, we have that $x_0 = 0$, $x_1 = pyr15/(lp15 + ls15+lh15)$, $x_2 = syr15/(ls15+lh15)$, $x_3 = hyr15/lh15$, $n_0 = lu15$, $n_1 = lp15$, $n_2 = ls15$, $n_3 = lh15$ and $\bar{H} = tyr15$.

Table 1
Two examples of the distribution of education by quintiles

	Education levels			Quintiles						G^h
	i	x_i	n_i	s	p_s	\hat{p}_s	\tilde{x}_s	u_s	Q_s	
Yemen (1975)	0	0	0.988	1	0.20	0.20	0	0	0	0.990
	1	5.2	0.005	2	0.20	0.40	0	0	0	
	2	4.5	0.005	3	0.20	0.60	0	0	0	
	3	2.0	0.001	4	0.20	0.80	0	0	0	
				5	0.20	1.00	0.098	0.098	1.0	
United States (1980)	0	0	0.009	1	0.20	0.20	1.898	1.898	0.161	0.080
	1	5.9	0.051	2	0.20	0.40	2.279	4.176	0.353	
	2	5.5	0.662	3	0.20	0.60	2.279	6.455	0.546	
	3	2.9	0.281	4	0.20	0.80	2.506	8.961	0.758	
				5	0.20	1.00	2.861	11.822	1.000	

Definitions: i is the education level (no schooling (0), primary (1), secondary (2) and tertiary (3)), x_i is the average schooling years of each educational level, n_i is the share of no schooling, primary, secondary and higher schooling attained by the population aged 15 years and over, s is the quintile, p_s is the share of the population in each of the five intervals, \hat{p}_s is the cumulative population share, \tilde{x}_s is the total schooling years attained by each of the quintiles, $u_s = \sum_{m=1}^s \tilde{x}_m$ and the cumulative share of education attained by each quintile is $Q_s = u_s / u_5$. As an example, in the case of the United States in 1980, since $n_0 + n_1 < 0.2$, the total schooling years attained by the first quintile (\tilde{x}_1) is given by $\tilde{x}_1 = n_0 x_0 + n_1 x_1 + (0.20 - n_1 - n_0)(x_1 + x_2) = 1.898$

Although Barro and Lee's data set is the best available source on human capital stocks for a large sample of countries to date, as Krueger and Lindahl (2000) or De la Fuente and Doménech (2001) have pointed out, the measurement errors for different education levels, due to the poor quality of the original sources, can be particularly substantial in some countries. To the extent that we use Barro and Lee's data set, we acknowledge the presence of some measurement errors which may distort the inequality variables we have computed.

Our data set includes 108 countries from 1960 to 2000, with a total of 935 observations. All countries for which human capital variables are available have been classified in seven different groups, and basic descriptive statistics of the Gini coefficients and the distribution of education by quintiles are shown in Table 2.

The second column of Table 2 (G^h) illustrates that South Asia countries are the group that, on average, have the largest human capital Gini coefficient (0.697). On the

Table 2
Average human capital inequality indicators by groups of countries

	G^h	Q_3	Bot_{20}/Top_{20}	$\Delta \ln G^h$	\bar{H}	G^y
Middle East & North Africa	0.583	0.165	0.032	-0.073	3.931	0.403
Sub Saharian Africa	0.637	0.119	0.005	-0.044	2.430	0.481
Latin America & the Caribbean	0.367	0.339	0.127	-0.026	4.784	0.494
East Asia & the Pacific	0.377	0.331	0.092	-0.068	5.558	0.405
South Asia	0.697	0.080	0.010	-0.041	2.400	0.349
Advanced Countries	0.208	0.455	0.362	0.003	7.940	0.339
Transitional Economies	0.223	0.447	0.299	-0.015	7.045	0.285

G^h is the human capital Gini coefficient, Q_3 is the third quintile, Bot_{20}/Top_{20} is the bottom to the top quintile, \bar{H} is the stock of human capital and G^y is the income Gini coefficient.

contrary, the countries with a more egalitarian distribution of human capital are the Advanced Countries with a mean of 0.208. With regard to the quintiles, the third column shows that the ranking among countries in terms of human capital equality, measured by the third quintile (Q_3), is equal to the one obtained with the Gini coefficient. However, the order differs with the ratio of the bottom quintile to the top one (column 4). Although South Asia countries show on average a larger Gini coefficient than Sub-Saharan African countries, the lowest 20% of the population receives more education in the former group than in the latter. As a result, South Asia is the region with the greatest inequality, measured by the Gini coefficient, whereas Sub Saharian Africa is the region with the greatest inequality, measured by the ratio of the bottom to the top quintile.

The fifth column ($\Delta \ln G^h$) indicates that all groups of countries, with the exception of Advanced Countries, have decreased the inequality in the distribution of human capital. The average schooling years of the population aged 15 years and over (\bar{H}) is displayed in the sixth column. It shows that the economies with a higher stock of human capital are also the countries in which education is more evenly distributed. In fact, the correlation between G^h and \bar{H} is very high (-0.90). However, Fig. 1 shows that the dispersion among both indicators increases substantially as the Gini index falls. We also find many countries that, in spite of having the same average schooling years, significantly differ in the distribution of education. According to recent World Bank figures, in the 80's India and Indonesia, both highly populated countries, had similar levels of income inequality. They also had similar levels of average years of schooling: approximately 3.6 years of formal education. However, as Fig. 1 shows, the distribution of education was quite different since the proportion of the population with no schooling and, at the other extreme, with a university education was much higher in India than in

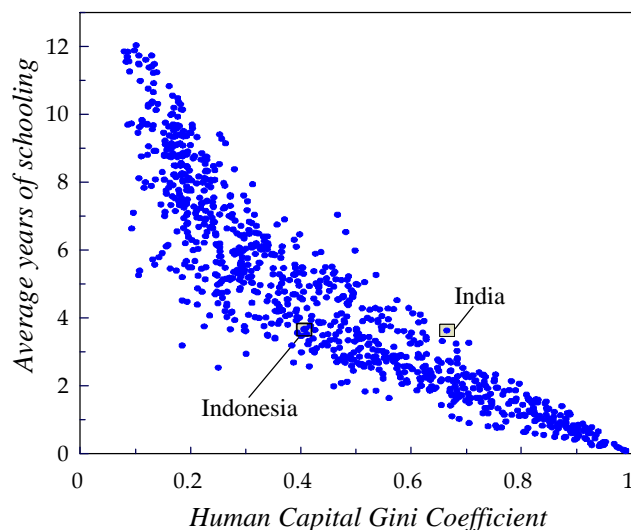


Figure 1: Human capital inequality and the level of human capital (average years of schooling).

Indonesia.

Finally, there is a surprisingly low correlation between the human capital and the income Gini coefficients. Comparing the second and the seventh columns, we can appreciate that the countries with the lowest and the greatest inequality in the distribution of education do not coincide with those in the distribution of income. These differences explain the low correlation between both inequality indicators (0.27) shown in Fig. 2.

2. Variations Within and Across Countries

This section explores the variability of human capital inequality measures 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?

To study the possible existence of a general within-country time trend during the period 1960-2000, as well as the existence of country specific effects, we consider the following simple linear trend model:

$$HCI_{it} = \alpha_i + \beta d_t + u_{it} \quad (4)$$

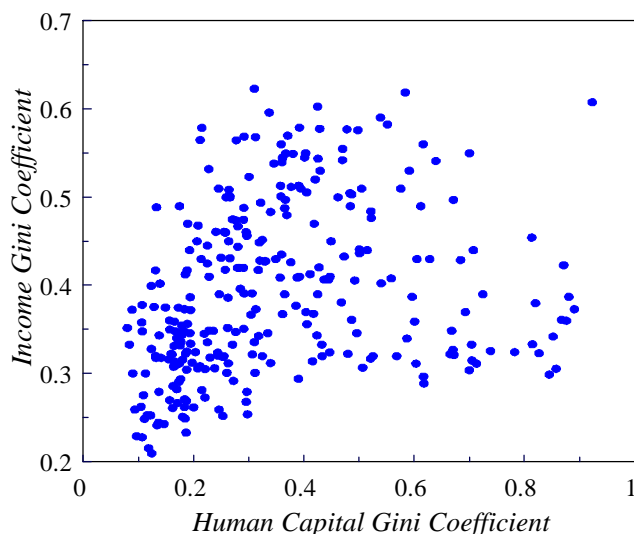


Figure 2: Income inequality and human capital inequality.

where HCI is a human capital inequality indicator (G^h and Bot_{20}/Top_{20}), i is the country, t the year and d a trend. As expected, the results indicate that the null hypothesis of equal country specific effects ($\alpha_i = \alpha, \forall i$) is rejected. Moreover, the coefficient for a general trend is negative for the Gini index (-0.021), positive for Bot_{20}/Top_{20} (0.007) and statistically significant in both cases. Therefore, the differences in the distribution of education across countries are substantial and, in general, countries have tended to reduce the inequality in human capital distribution over the period under study.

The preceding exercise shows how the mean of these indicators has evolved over time, but we also want to analyze how the dispersion and relative position of each country has changed from 1960 to 2000. The easiest way to test the constancy in the dispersion of the Gini coefficient is through a time plot of its standard deviation. Nevertheless, the standard deviation is not enough to characterize the distribution when it is not a normal one. In particular, the Bera-Jarque test rejects the null hypothesis of normality of the distribution of the Gini coefficient and the ratio of the bottom to the top quintile. For this reason, in Fig. 3 we have represented the non-parametric estimation of the density functions of G^h using a truncated gaussian kernel for a distribution in the interval $[0, 1]$.⁶

⁶ We thank F. J. Goerlich for providing the programme that implements such a procedure. The main result shown in Figure 3 is robust to changes in bandwidth parameters.

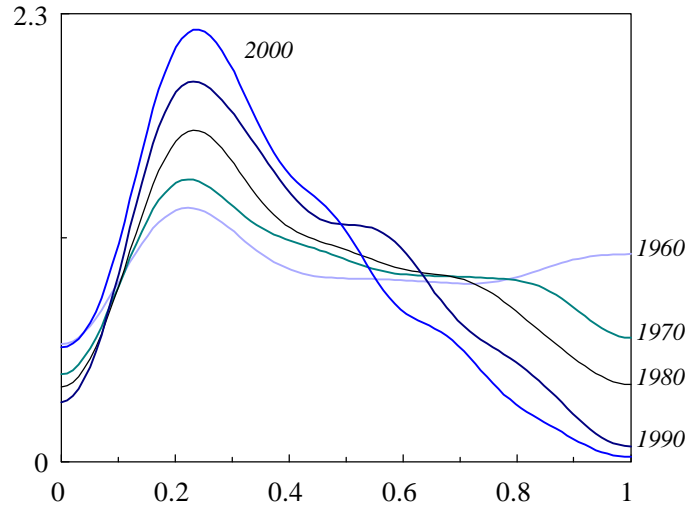


Figure 3: Density functions of the Gini coefficient 1960-2000.

As we can see, the distribution of G^h in 1960 clearly shows two modes, but slowly the density concentrates around a Gini coefficient of 0.25. Thus, although the distribution is clearly not normal, in 2000 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 human capital inequality shall be analyzed thoroughly. In particular, with the purpose of analyzing the relative position of each country and its evolution over time, we take into account the concept of Quah's probability transitional matrix. Quah (1993, 1996) 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 probability transitional matrix indicates the probability that an economy in income group i transits to income group j between two different years. The same qualitative information has been represented in Fig. 4. In this figure, we plot the relative position of the Gini index across countries in 2000 against their relative position in 1960, dividing the sample into the five intervals considered by Quah. The cutting points between intervals are the logs of $1/4$, $1/2$, 1 and 2 times the (geometric) average of the Gini coefficient ($\overline{G^h}$). These intervals allow us to confirm the existence of convergence or polarisation of the Gini coefficient. If countries had converged, they should have changed from their initial intervals in 1960 to the one around the average in 2000. On the contrary, if there had been a polarisation in human capital Gini coefficients,

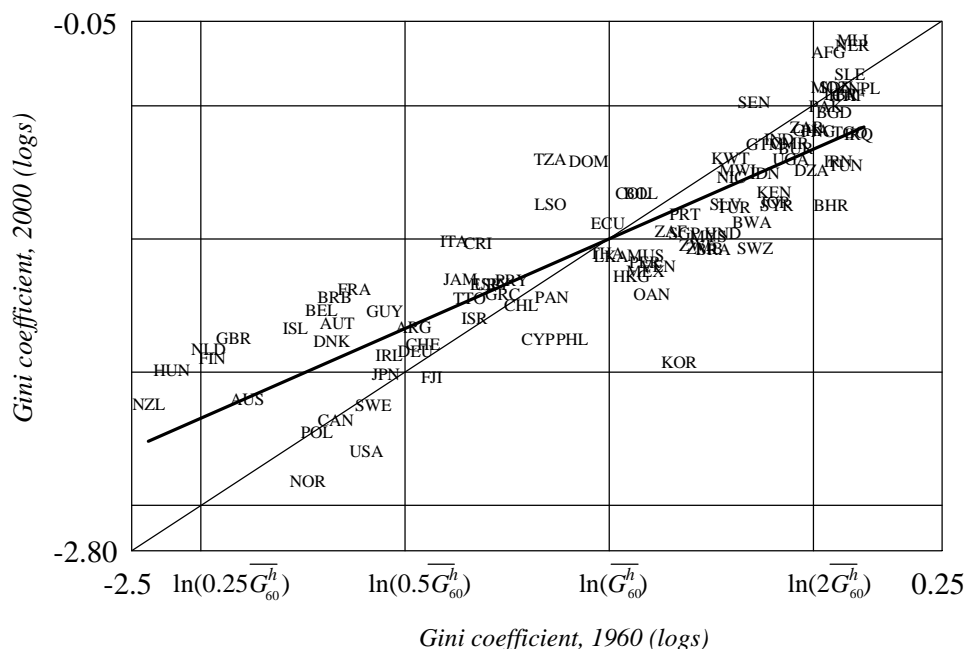


Figure 4: Convergence of the human capital Gini coefficient (G^h) in logs.

countries should have changed from their initial intervals to the extremes. The diagonal simply reflects the logs of the values of the Gini index in 1960 multiplied by the sample average rate of growth between 1960 and 2000. Thus, countries win or lose in relative positions according to their vertical distance to the diagonal. As we can see in Fig. 4, some countries that showed a high inequality in 1960 (that were in the fifth interval) have reduced inequality, moving to the fourth interval by 2000. Likewise, some countries that were in the fourth interval in 1960 have reduced inequality, moving to the third interval by 2000, as in the case of Korea, Taiwan and Hong Kong, which are good examples of an important reduction in human capital inequality. On the contrary, some OECD countries have worsened their relative positions.

Finally, Fig. 4 also shows the adjusted values of the Gini index in 2000 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 observe in this figure, it seems that during the period 1960 to 2000 there has been a process of convergence in the values of the Gini coefficients since the slope of the regression line

is smaller than the slope of the diagonal line (the estimated coefficient is equal to 0.673 with a t -ratio equal to 16.49).

3. Human Capital Inequality and Economic Growth

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 results of this section should be seen as a first attempt to evaluate the effects of human capital inequality upon economic growth using these measures rather than as a definitive analysis of the determinants of growth or as a test of any particular model. Additionally, although we are aware of some recent developments in the econometric analysis of economic growth and convergence, such as the contributions of Islam (1995), Caselli, Esquivel and Lefort (1996), and Lee, Pesaran and Smith (1997, 1998), our approach relies deliberately on standard cross-section and pooling regressions in order to facilitate the comparison with previous results in related literature.⁷

The data used in our growth regressions comes from Barro and Lee (1994, 2001) with the exception of the variables concerning inequality. With regard to 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 (close to 1960), the problems with the availability of high quality income Gini data restrict us to including this variable as an average.⁸

In our initial regression, the average growth rate of per capita income from 1960 to 1990 ($\Delta \ln y$) is the dependent variable and income inequality is included as an explanatory variable along with the logs of human capital accumulation ($\ln s_h$), defined as the total gross enrollment ratio for secondary education (taken from UNESCO), physical capital accumulation ($\ln s_k$), defined as the ratio of real domestic investment to real GDP, the black market premium (BMP) to control for government distortions of markets, and

⁷ For example, using panel techniques to control for time invariant country-specific effects, Forbes (2000) gets very different results of the effects of income inequality on economic growth to the ones obtained by Alesina and Rodrik (1994), Perotti (1996), Persson and Tabellini (1994), or Deininger and Squire (1998).

⁸ The inclusion of the income Gini at the beginning of the period significantly reduces the size of the sample. As the variability of this coefficient is very low throughout the whole period (see Li, Squire and Zou (1998)) the inclusion of this variable as an average does not change the main results.

Table 3
Cross-section regressions

	$\Delta \ln y$						$\ln s_k$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Constant</i>	0.122 (5.19)	0.142 (7.20)	0.147 (4.65)	0.133 (7.96)	0.129 (7.05)	0.118 (5.82)	-1.208 (1.89)	1.969 (1.75)	1.653 (1.33)
$\ln y_{60}$	-0.011 (4.14)	-0.011 (5.17)	-0.013 (6.01)	-0.011 (5.95)	-0.011 (6.01)	-0.010 (4.82)	-0.015 (0.21)	-0.077 (1.06)	-0.082 (1.15)
$\ln s_h$	0.006 (2.01)	0.006 (2.46)	0.006 (2.53)				0.201 (2.08)	0.285 (3.17)	0.279 (2.94)
$\ln s_k$	0.005 (1.35)	0.007 (2.65)	0.005 (1.74)						
G^y	0.038 (2.12)					0.033 (1.95)	0.846 (1.61)		
G_{60}^h	-0.021 (2.76)	-0.017 (3.08)	-0.016 (2.70)	-0.028 (6.37)	-0.022 (2.21)	-0.030 (5.89)	-0.717 (2.93)	-0.849 (3.86)	-0.604 (1.67)
<i>BMP</i>	-0.004 (1.74)	-0.006 (2.81)	-0.006 (3.36)	-0.005 (3.07)	-0.006 (3.11)	-0.003 (1.37)	-0.022 (0.20)	-0.266 (1.60)	-0.268 (1.60)
$\ln(n + 0.05)$			-0.004 (0.39)					0.727 (2.52)	0.672 (2.35)
g			-0.051 (2.54)	-0.063 (3.38)	-0.061 (3.25)	-0.063 (3.01)		-1.593 (2.17)	-1.518 (2.08)
$\ln H_{60}$					0.002 (0.71)				0.076 (0.83)
<i>Laam</i>	-0.019 (4.67)	-0.014 (5.78)	-0.016 (5.07)	-0.020 (8.34)	-0.020 (8.34)	-0.022 (6.24)	-0.298 (2.53)	-0.346 (4.15)	-0.347 (4.17)
<i>Safrica</i>	-0.022 (4.18)	-0.018 (5.01)	-0.018 (5.05)	-0.026 (8.32)	-0.026 (8.38)	-0.028 (6.52)	-0.243 (1.12)	-0.093 (0.49)	-0.103 (0.55)
<i>Asiae</i>	0.019 (3.90)	0.019 (4.35)	0.017 (3.75)	0.018 (3.56)	0.017 (3.23)	0.018 (3.17)	0.011 (0.10)	-0.091 (0.81)	-0.119 (1.07)
\overline{R}^2	0.744	0.771	0.789	0.758	0.756	0.756	0.578	0.706	0.704
<i>N.obs.</i>	67	83	83	83	83	67	67	83	83

Note: Cross-country regressions. White's heteroscedasticity-consistent t ratios in parentheses. Explanatory variables: per capita income in 1960 (y), total gross enrollment ratio in secondary education (s_h), the investment rate (s_k), the income Gini coefficient (G^y), the human capital Gini coefficient in 1960 (G^h), the black market premium (*BMP*) in 1960, average population growth (n), total years of schooling of the population aged 15 and over in 1960 (H_{60}) and public consumption (g , from PWT 5.5). *Laam*, *Safrica* and *Asiae* are regional dummies. Dummies for Botswana and Philippines in cols. (1) to (6), Bangladesh in col. (7), and Mozambique in cols. (8) to (9) are included, since their residuals exceed more than three times the standard error of the estimated residuals.

initial per capita income ($\ln y$). The results (not shown here) 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.⁹ Nevertheless, this result is not robust to the inclusion of additional variables to the set of regressors. In particular, as obtained by Deininger and Squire (1998), the coefficient of G^y is not statistically significant when we include regional dummies, which capture permanent and specific characteristics of the regions that otherwise could bias the coefficients of some explanatory variables. Moreover, when we add human capital inequality in 1960, measured by the human capital Gini coefficient (G^h) in this basic growth equation, the coefficient of G^y even becomes positive, as shown in column (1) of Table 3, whereas the coefficient of G^h is negative and significant. These initial results suggest, therefore, that the negative relationship between income inequality and growth, obtained in previous studies, is not robust to the inclusion of other variables in the regression.

In column (2) of Table 3, income inequality has been excluded from the set of explanatory variables. Although our human inequality indicator may contain some measurement errors as we have mentioned earlier, in contrast to the results for income inequality, the coefficient of human capital inequality is again negative and statistically significant when regional dummies are present. A similar result is obtained in column (3) when we include other explanatory variables often considered in the literature: the log of the average population growth (as in Mankiw, Romer and Weil, 1992, augmented by the rate of technical progress and the depreciation rate, assumed to be 0.02 and 0.03, respectively) and public consumption over GDP.

The preceding regressions consider the direct effect of inequality on growth, but it is also possible that inequality variables are related indirectly to economic growth through the accumulation of factors. Column (4) shows 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 bigger negative effect on the economic growth rates, suggesting that the indirect effects through the accumulation rates are also very important. However, given the high correlation between human capital inequality and its stock, it is possible that G^h may be picking up the effect of the level of human capital on growth. In column (5) we test this hypothesis. Although the coefficient is now smaller than in column (4), the results suggest that the effects of the distribution of human capital are important and significant. Column (6) shows the results of adding income inequality to the specification estimated in column (4): the coefficient of G^y is again positive whereas

⁹ A negative relationship between income inequality and growth can be found in Alesina and Rodrik (1994), Persson and Tabellini (1994), Clarke (1995) or Perotti (1996).

that of G^h is negative and statistically significant. Taking these results together, the coefficient of human capital inequality ranges approximately between -0.015 and -0.03 . As G^h fell by 0.10 points on average from 1960 ($G_{1960}^h = 0.41$) to 2000 ($G_{2000}^h = 0.31$), the effects on the average annual growth rates range between 0.15 and 0.30%.

An alternative way of analyzing the indirect effects of human capital inequality on growth is pursued in columns (7) to (9), using now the log of accumulation of physical capital (s_k) as the dependent variable. In column (7) we observe that initial human capital inequality has a significant and negative effect on physical capital accumulation. On the contrary, the results concerning income inequality are quite different since the effect of the income Gini coefficient on physical capital accumulation seems to be positive. Columns (8) and (9) show that the negative effects of human capital inequality on the investment rate survives to the inclusion of other variables such as population growth, public consumption and the initial stock of human capital.

Finally, we have analyzed the robustness of these results.¹⁰ First, all the results hold when we examine their sensitivity to the exclusion of atypical observations in our sample. Second, we test if results in Table 3 hold with pooled data. Third, extending the data in its temporal dimension allows us to use lagged variables as instruments to control for the existence of endogenous explanatory variables, such as the accumulation rates. The regressions with pooled data confirm the results obtained in the previous exercises: human capital inequality has a negative and statistically significant effect upon growth mainly through the investment rate. Fourth, we have also analyzed the robustness using different measures of inequality. In particular, the results with the third quintile as a measure of equality are quite similar to the ones obtained with the Gini coefficient. Finally, these negative effects of human capital inequality are also supported when we do the same regressions for a sample of developing countries only.

4. Conclusions

The main objective of this paper has been to provide indicators of human capital inequality for a large sample of countries and years, and to analyze 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. One of the main advantages of these indicators is that they may conveniently complement the information provided by income inequality measures.

Using these new indicators two main findings are obtained. First, the variability of human capital inequality indicators is greater across countries than within each country.

¹⁰ The results are available upon request.

Nevertheless, as a result of a general reduction in human capital inequality, a process of convergence in human capital equality has taken place. Second, whereas the negative effect of income inequality on economic growth rates is not robust to the inclusion of regional dummies to the set of regressors, the cross-country and pool regressions suggest that there is a negative effect of human capital inequality on economic growth rates. This result is robust to changes in the explanatory variables, the exclusion of atypical observations, the use of instrumental variables to control for endogeneity problems and the utilization of different measures of human capital inequality.

In short, these findings indicate that education inequality is associated with lower investment rates and, consequently, lower income growth. Countries that in 1960 showed greater inequality in the distribution of education have experienced lower investment rates than countries which showed less inequality. These lower investment rates have in turn meant lower income growth rates. Policies, therefore, conducted to promote growth should not only take into account the level but also the distribution of education, generalising the access to formal education at different stages to a wider section of the population.

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