A REASSESSMENT OF THE RELATIONSHIP BETWEEN INEQUALITY AND GROWTH: WHAT HUMAN CAPITAL INEQUALITY DATA SAY? *

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ABSTRACT

This paper studies the empirical relationship between inequality and economic growth. It estimates a dynamic panel data model that controls for fixed effects and, therefore, solves the problem of omitted variable bias present in cross-section regressions. Forbes'(2000) results suggest that income inequality and economic growth are positively related when country specific effects are taken into account. This paper shows that this result holds even controlling for education inequality. However, neither the first difference nor the system GMM estimator, which seems to perform better in growth regressions, support a positive association between education inequality and economic growth. On the contrary, an increase in human capital inequality is related to lower subsequent growth rates not only in the long-term across-countries but also in the short-term within a country. In particular, the negative relationship between human capital inequality and growth is mainly due to a discouraging effect on the physical capital investment rates and, in line with the model of De la Croix and Doepke (2003), through a channel that connects inequality an fertility decisions.

JEL classification: O15; 040; O25

Keywords: Human capital and income inequality; Economic growth; Dynamic panel data model.

1 Introduction

In the early 1990s some theoretical models analysed the effect that inequality in the distribution of income and wealth may exert on economic growth rates. Among the most representative studies in this literature are the papers by Alesina and Rodrik (1994), Bertola (1993), Galor and Zeira (1993) or Persson and Tabellini (1994). Although these studies approached the relationship between inequality and growth in different ways, all of them found a discouraging effect of inequality in the distribution of wealth on growth rates.

The theoretical results of these models gained significant relevance since their conclusions were supported by some empirical evidence. Alesina and Rodrik (1994), Persson and Tabellini (1994), Clarke (1995), Perotti (1996) or Deininger and Squire (1998), among others, found a negative relationship between income inequality and economic growth. The empirical evidence was mainly based on the estimation of a convergence equation in which an income inequality variable was added to the set of the explanatory variables to explain the differences in growth rates across countries. Due to the scarcity of data on income inequality that includes several periods, most of these studies analysed, in a cross-section of countries, the effect of inequality in the distribution of income in 1960 on the average growth rate of per capita income in the period 1960-1990.

With the appearance of Deininger and Squire's (1996) data set, the quantity and quality of income inequality data improved considerably with respect to previous sources. This new data set has allowed that more recent empirical studies to use the temporal dimension of the data to estimate panel data models. However, the extension of the data set, to incorporate a temporal dimension, resulted in the questioning of a negative relationship between inequality and growth obtained in previous studies. For example, in a panel of countries Barro (2000) does not find a significant statistical relationship between inequality in the distribution of income and economic growth rates when the sample includes all the countries for which there are available data on income inequality measures. In addition, when the sample is divided between rich and poor countries, Barro (2000) finds a negative relationship between both variables in the sample of poor countries and a positive relationship in the sample of rich countries.

A very important study in this area is the paper of Forbes (2000). In order to control for country specific effects, Forbes (2000) estimates a panel data model using the generalized method of moments proposed by Arellano and Bond (1991). This study obtains the most surprising results since it suggests that in the medium and short term an increase in the level of inequality in the distribution of income in a country has a positive and significant relationship with its subsequent economic growth rates, challenging the robustness of the initial results that showed the existence of a negative relationship between inequality and growth.[1]

[1] Estimating also a dynamic panel data model but using regional data of the American States, Panizza (2002) does not find evidence of a positive correlation between changes in income inequality and changes in growth. In addition, he finds that the relationship between income inequality and growth is not robust. He shows that the relationship depends on the

Some studies have argued that the lack of consistency in the results is due to the fact that empirical studies estimate a linear model whereas the true relation is not linear (e.g. Banerjee and Duflo (2003)). Other papers object that income inequality data may be a poor proxy for wealth inequality and, in order to palliate this shortcoming, they use the distribution of other assets to analyse the effect of inequality on growth. For example, Alesina and Rodrik (1994) or Deiniger and Squire (1998) also use data on land inequality to proxy wealth inequality. The results show that the effect of land inequality on economic growth in cross-sectional regressions is more robust than that of income inequality. However, the data on land inequality is very limited and it can not be used to estimate a dynamic panel data model to check if cross-sectional results hold when we control for specific characteristics of countries whose omission may bias the estimated coefficients.

Other important component of wealth as well as of the growth rate is the stock of human capital. In fact, in some theoretical models the source of inequality is mainly driven by inequality in the distribution of human capital (e.g. Glomm and Ravikumar (1992), Saint-Paul and Verdier (1993) or Galor and Tsiddon (1997)). In addition, the role played by human capital accumulation is also present in most of the models that analyse the relationship between inequality and growth. Under imperfect credit markets and indivisibilities in the accumulation of human capital, Galor and Zeira (1993) find that the greater the number of individuals with inheritances below a threshold level, the lower the average human capital in the economy and therefore the lower the growth rate. Recently, De la Croix and Doepke (2003) have developed a model that analyses a new link between inequality and growth. This channel, based on differences in fertility rates, also gives an important role to the distribution of education in determining the growth rates of the economies. In their model households with lower human capital choose to have a higher number of children and less education for them, which increases the weight of lower skill individuals in the future and therefore lowers the average level of human capital and growth rates in the economy.

The important role of education inequality in determining the growth rates has also been pointed out by the empirical paper of Castello and Domenech (2002). This study includes, in addition to income inequality, the distribution of education in the analysis of the relationship between inequality and growth. The interesting result is that the initial distribution of education seems to play a more robust role than that of the distribution of income in the estimation of cross-section regressions, suggesting that it is education inequality instead of income inequality what has had a discouraging effect on the growth rates. In particular, the negative effect of income inequality on economic growth, found in previous studies, disappears when they include dummies for Latin American, Sub-Saharan Africa and East Asian countries, which implies that income inequality might be picking up specific characteristics of the regions. On the contrary, human capital inequality has a negative and quite robust effect on per

econometric specification and the method used to measure inequality.

capita growth and the investment rate even controlling for regional dummies.

In order to compare the effect of human capital inequality with that of income inequality obtained in previous studies, Castello and Domenech (2002) estimate a cross-section growth regression. However, there are mainly two inconsistency sources in cross-section growth regressions. The first one is that cross-section estimations fail to control for specific characteristics of countries such as differences in technology, tastes, climate or institutions whose omission may bias the coefficient of the explanatory variables. In particular, in the papers that analyse empirically the implications of the Solow model the omitted variable captures the initial level of technology. The second one regards with the inadequate treatment of some explanatory variables that, according to the theory, should be consider as endogenous.[2] In addition, controlling for fixed effects also allows us to analyse how increases in inequality within a country are related to changes in growth within that country.

Controlling for fixed effects has been an important issue in cross-country growth regressions since it has challenged some important results.[3] Thus, given that Castello and Domenech's (2002) findings provide new perspectives to the relationship between inequality and growth it would be necessary to deep in such relationship using more appropriate econometric techniques. In particular, it is important to analyse whether their results hold when we estimate the model controlling for country specific effects. Hence, the aim of this study is to answer the following question: Does the negative relationship between human capital inequality and economic growth, found in cross-section regressions, hold when we estimate a dynamic panel data model that controls for fixed effects?.

To answer this question our starting point is Forbes´ (2000) which uses the same specification as Perotti (1996). In order to control for country specific effects Forbes estimates a dynamic panel data model using the GMM estimator proposed by Arellano and Bond (1991). However, one challenge is that the human capital and the income Gini coefficients show very little within country variation. Since the fixed effects and any other difference estimator remove all cross-country variation, the lack of within country variation may exacerbate the bias due to measurement error. This is the reason argued by Barro (2000) to use three-stage least squares which considers the specific error term as random. Nevertheless, this technique only provides consistent estimators under the as-

[2] The problem of the omitted variable has been treated differently in the literature. Whereas Mankiw et al. (1992) include the initial level of technology in the error term and make the identifying assumption that the error is independent of the explanatory variables, Islam (1995) considers that it is a strong assumption and uses fixed effects to eliminate the country specific effect. However, Caselli et al. (1996) point out that the country-specific effect and the log of the lagged income are necessarily correlated. Then, they use a GMM estimator that eliminates the country-specific effect by taking first differences. This paper also acknowledges the issue of endogeneity and uses the levels of the right hand side variables lagged at least two periods and all further lags to instrument the endogenous regressors.

[3] Some known examples are Caselli et al. (1996) who, estimating a dynamic panel data model that controls for fixed effects, obtain a convergence rate about 10 per cent per year instead of the traditional 2 per cent found in cross-section regressions or Forbes (2000) that obtains a positive and statistically significant relationship between income inequality and economic growth instead of the negative one found in cross-section studies.

sumption of no correlation between the specific error term and the explanatory variables, assumption that does not hold in a dynamic panel data model as the one we are supposed to estimate.

Being aware that in a dynamic panel data model the fixed effect is necessary correlated with at least one of the explanatory variables, many studies have applied the traditional GMM estimator proposed by Arellano and Bond (1991). However, the first difference GMM estimator has some shortcomings in the estimation of a growth regression. First, the variables included in growth regressions such as the level of income or schooling variables are highly persistent. This fact implies that by taking first differences almost all of the variation in the data, which comes from variability across-countries, disappears. Second, given that most of the variability in the data disappears, taking first differences may increase the measurement error bias by increasing the variance of the measurement error relative to the variance of the true signal. Third, under persistent variables the lagged levels can be poor instruments for the variables in differences.

In this paper we do not only take into account the problems associated with the first difference GMM estimator but also consider other improvements with regard to previous studies. First, in addition to use the first-difference GMM estimator we also report the results of the system GMM estimator which has been proved to perform better in growth regressions (see Bond et. al. (2001)) and has not been utilized to analyse the relationship between inequality and growth. The technique proposed by Arellano and Bover (1995) and Blundell and Bond (1998) partially solves the problems associated with the first difference GMM estimator. The system GMM estimator displays consistent estimators and allow us, under some assumptions, to use the variables in differences as instruments in a level equation. The idea of this estimator is to combine in a system of equations regressions in differences with regressions in levels. The use of this new estimator is important because we can check if the challenging results of Forbes (2000) holds with the use of a more appropriate econometric technique. Second, this paper uses human capital inequality variables in addition to income inequality measures. Apart from their intrinsic interest, human capital inequality variables can also complement the information provided by income inequality measures, specially in developing countries where income inequality data are scarce. Moreover, income inequality measures have been subject to many criticisms due to the poor quality of available data.[4] Since the econometric techniques that control for fixed effects may exacerbate the measurement error bias, the results concerned only to income inequality variables could lead to mistaken conclusions if the measurement errors in income inequality variables are important. Third, we utilize the latest data set on income inequality variables which allows us not only to extend the time period but also to include a few more countries in the analysis. Finally, although the new data set increases the observations of the income Gini coefficient, the available data on

[4]For objections about the quality of income inequality variables see Atkinson and Brandolini (2001).

income inequality variables are still scarce. For this reason in the second part of the paper we focus on the analysis of human capital inequality and economic growth. This exercise is beneficial for two reasons. On the one hand, it allows us to almost double the number of countries in the analysis with the particularity that the new countries are mainly developing countries, which have been scarce in all the studies that focus on income inequality and growth. On the other hand, the greater number of observations is useful to estimate a more complete and proper specification, similar to the one used by Barro (2000), that can be used to study some ways through which inequality may influence growth.

The main findings of the paper are as follows. First, even controlling for human capital inequality, the first difference GMM estimator supports the positive and statistically significant association between income inequality and economic growth found in Forbes (2000). However, the coefficient of the income Gini index stops being statistically significant at the standard levels when the model is estimated with the system GMM estimator which, according to Bond *et al.* (2001), seems to perform better in the estimation of growth models. Second, controlling for fixed effects does not remove the negative association between human capital inequality and economic growth found in cross-section regressions. In particular, both the first difference and the system GMM estimators display a negative and statistically significant relationship between human capital inequality and economic growth. Therefore, greater human capital inequality is related to lower subsequent growth rates not only in the long term across-countries but also in the short term within a country. Third, the evidence suggest that this negative relationship is due to a discouraging effect of human capital inequality on the investment rates and to a promoting effect on the fertility rates.

The remainder of this article is organized as follows. Section 2 shows the model to be estimated and discusses some econometric issues. Section 3 estimates a model in line with Forbes with some improvements. In order to increase the number of observations, Section 4 focuses on the analysis of human capital inequality and economic growth, which allows us to estimate a more complete and proper specification similar to the one used by Barro (2000). Finally, Section 5 offers some conclusions.

2 The model and the data

2.1 The model

Most of the empirical studies that have analysed the relationship between income inequality and economic growth have focused on cross-section growth regressions in which an income inequality variable is added to the set of explanatory variables in a convergence equation. In most of these regressions the dependent variable is the average growth rate of real per capita GDP between 1960 and 1985.

In the set of regressors, the initial real GDP per capita is a common explanatory variable included in all studies. With regard to the income inequality variable, Alesina and Rodrik (1994) or Deininger and Squire (1998) measure inequality through the Gini coefficient, Persson and Tabellini (1994) use the percentage of income of the third quintile and Perotti (1996) includes the share of the third and fourth quintile. The remaining variables also differ from one study to the other. The initial level of education sometimes is measured as a flow through the enrollment rates and in other occasions as a stock through the average years of schooling. Other controls include dummies for democratic countries, the black market premium or the PPP value of the investment deflator relative to the United States. A general specification that represents these estimated models could be written as follows:

$$(\ln y_{i,t} - \ln y_{i,t-\tau})/\tau = \beta \ln y_{i,t-\tau} + \gamma Inequality_{i,t-\tau} + X_{i,t-\tau}\delta + \mu_{it} \tag{1}$$

where $y_{i,t}$ is the real GDP per capita in country i measured at year t,[5] τ is the number of years of the whole period, $Inequality_{i,t-\tau}$ measures income inequality in country i at the beginning of the period- usually in 1960, $X_{i,t-\tau}$ is a matrix including k explanatory variables, μ_i is the error term and β, γ and δ represent the parameters of interest that are estimated .

Despite using different explanatory variables, all these studies obtained a negative and statistically significant coefficient for the income inequality variable. This suggests that, other things equal, those countries with higher inequality in the distribution of income in 1960 experienced, on average, lower per capita income growth rates during the period 1960-1985.

One of the main criticisms of this kind of regressions is that cross-section estimators may be biased due to omitted variables in the model. In particular these regressions fail to control for tastes, the level of technology, resource endowments, climate, institutions or any other variable specific to every country that may be an important determinant of the growth rates and may be correlated with the explanatory variables included in the estimated equation. Measuring these variables is troublesome because sometimes they are unobservable. However, if these variables are constant over time we can control for them including a country specific effect in the model. To do so we could detach the error term in (1) into three different components:

$$\mu_{it} = \xi_t + \alpha_i + \varepsilon_{it} \tag{2}$$

where ξ_t is a time specific effect, α_i stands for specific characteristics of every country that are constant over time and ε_{it} collects the error term that varies across countries and across time. Using (2) we could rewrite (1) as follows:

[5] In most studies the initial level of income in the set of regressors is included without logs and others like Barro (2000) also include the log of per capita income squared to pick up a non linear convergence effect.

$$\ln y_{i,t} = \widetilde{\beta} \ln y_{i,t-\tau} + \widetilde{\gamma} Inequality_{i,t-\tau} + X_{i,t-\tau}\widetilde{\delta} + \widetilde{\xi}_t + \widetilde{\alpha}_i + \widetilde{\varepsilon}_{it} \tag{3}$$

If we consider τ different from one we have that $\widetilde{\beta} = \tau\beta + 1$, $\widetilde{\gamma} = \tau\gamma$, $\widetilde{\delta} = \tau\delta$, $\widetilde{\xi}_t = \tau\xi_t$, $\widetilde{\alpha}_i = \tau\alpha_i$ and $\widetilde{\varepsilon}_{it} = \tau\varepsilon_{it}$.

The best technique to estimate equation (3) depends on the assumptions we can make about the error term and its correlation with the explanatory variables. If we assume that the regressors are strictly exogenous and that the country specific error term is not related to the explanatory variables then the Generalized Least Square estimator is consistent and efficient.[6] If we can not assume that α_i is random we should use the fixed effect estimator which removes the fixed effect by substracting time averages of every country. However, to use any of these techniques we need to assume that the regressors are strictly exogenous and the presence of a lagged explanatory variable in equation (3) invalidates such assumption.[7]

Most of the studies concerned with the econometric problems stated above have used the Generalized Method of Moments developed in Arellano and Bond (1991) to estimate dynamic panel data models since, under the assumption of no serial correlation in the error term, the estimators provided by this methodology are consistent and efficient. The idea is to remove the source of inconsistency by taking first differences of the original level equation to eliminate the country specific effect. In addition, by using the levels of the explanatory variables lagged at least two periods as instruments, this estimator also solves the problem of endogenous explanatory variables quite common in empirical growth models.

However, more recent developments have pointed out that under a large autoregressive parameter and few time series observations, the lagged levels of the series are weak instruments for first differences. Alonso-Borrego and Arellano (1999) find that the shortcoming of weak instruments translate into large finite sample bias. A solution to this problem comes from Arellano and Bover (1995) who develop a new estimator that, in addition to use the lagged variables as instruments for first differences, also uses the information provided by lagged differences to instrument the equation in levels. Monte Carlo simulations provided by Blundell and Bond (1998) show that the extended GMM estimator improves the precision compared to the first difference GMM estimator.

The extended GMM estimator, usually called system GMM, has not been utilized to analyse the relationship between inequality and growth. The use of the system GMM estimator will allow us, not only to provide efficient and consistent estimators for the coefficient of the human capital Gini index, but also to check if the positive relationship between income inequality and economic

[6] Strictly exogeneity implies that $E(W_{it}\varepsilon_{is}) = 0 \;\forall\; s,\, t$. Where W_{it} is a vector that includes all the explanatory variables.

[7] Note that $E(\ln y_{i,t-1}\varepsilon_{i,t-1}) \neq 0$. If we assume that the errors are not serially correlated the variable $\ln y_{i,t-1}$ is predetermined since $E(\ln y_{i,t}\varepsilon_{i,s}) = 0 \;\forall\; s > t$. Note also that $E(\ln y_{i,t-1}\alpha_i) \neq 0$.

growth, found with the first-differences GMM estimators, is biased due to the use of weak instruments.

2.2 The data

The results in Forbes (2000) have challenged the traditional view of a negative relationship between inequality and growth, even though they refer to the short and medium term and within a country. Hence, in the next Section, in addition to analysing the relationship between human capital inequality and economic growth controlling for fixed effects, we also ask if Forbes' results hold when we extend the model to include the human capital Gini coefficient. Therefore, the benchmark model to analyse the relationship between inequality and economic growth in the following Section is the specification used by Forbes (2000), which employs the same explanatory variables as Perotti (1996). The dependent variable is the growth rate of per capita income measured in constant prices ($dlny_{i,t}$). The average growth rate is defined over five-year intervals measured as the average growth rate from 1966 to 1970 for the first period, from 1971 to 1975 for the second period and so on. The set of regressors include the log of per capita income ($lny_{i,t-\tau}$), the income Gini coefficient ($Gini^{y}_{i,t-\tau}$), the human capital Gini coefficient ($Gini^{h}_{i,t-\tau}$), the average years of secondary schooling in the female population ($educf_{i,t-\tau}$), the average years of secondary schooling in the male population ($educm_{i,t-\tau}$) and the current price level of investment ($pi_{i,t-\tau}$). All the explanatory variables include observations starting in 1960 and finishing in 2000, except for the income Gini coefficient, whose first observation starts in 1965 and the last ends in 1995. Therefore, the inclusion of the income Gini coefficient restricts the analysis to the period 1965-2000 when no instrumental variables are used and to the period 1970-2000 when the explanatory variables are instrumented with their corresponding lags.

The sources of the data used are as follows.[8] The data on real GDP per capita and the current price of investment are taken from PWT 6.1 by Heston, Summers and Aten. The income Gini coefficient is from Deininger and Squire's (1996) data set and updated by the World Bank. Under the same premise of including only "high quality" data, we broaden the observations used by Forbes (2000) in two directions. On the one hand, we extend the income inequality data up to 1995. On the other hand, we add a few more countries. The observations used by Forbes (2000) and the new sample used in this study are displayed in Table 1. Even though we can include only ten more countries, Table 1 shows that most of them are developing countries and five of them are in Africa. This enlargement is a further step to achieve a data set that represents all areas in the world, some of them with no observation in Forbes' sample. On balance, there is a total of 55 countries with at least two observations of the income Gini index. The source of the human capital inequality variables is Castello and Domenech (2002) and the education variables are from the latest Barro and Lee' (2001)

[8] See the Appendix for a more exhaustive definition of variables and sources.

data set.[9]

The explanatory variables are measured at the end of period $t-\tau$. This means that, for example, the average per capita income growth rate in the period 1981-1985 is regressed on the explanatory variables measured at the end of the previous period- 1980.

Even though we have extended the income inequality data set, the availability of income inequality measures compared to other variables is still scarce. For instance, human capital inequality measures are available for 108 countries over the period 1960-2000 with a total of 935 observations. The availability of these data set that includes a greater number of observations may be used to estimate a more complete specification in line with Barro (2000). The estimation of a broader specification has some advantages compared to the parsimonious specification estimated in Forbes (2000) and Perotti (1996). On the one hand, increasing the number of explanatory variables will reduce the problem of omitted variables bias. On the other hand, a broader specification that includes in the right hand side variables such as the investment and the fertility rates can be used to check some of the channels through which inequality may influence growth. Hence, in Section 4 we will estimate a broader specification restricting the analysis to the relationship between human capital inequality and economic growth.

3 Estimation results

This section presents the estimation results of an economic growth equation where income and human capital inequality enter in the model as explanatory variables. As mentioned above the benchmark model for this Section is the one used by Perotti (1996) and Forbes (2000) with the addition of education inequality in the set of explanatory variables. In spite of being the dynamic panel data model the main aim of this paper, we start with the estimation of the cross-section model for three reasons. First, we can compare the results of cross-section and panel estimators and attribute the differences to the underlying econometric models and not to the use of different samples, different controls or different data sets. Second, we can check if Castello and Domenech´s (2002) findings hold in a different specification that includes two controls for the average years of education. Finally, and more important, in the estimation of a dynamic model whereas cross-section estimators are biased under the presence of fixed effects, the first difference GMM and the fixed effects estimators may also be biased if the variance of the measurement error is high relative to the variance of the true regressor. In fact, using Monte Carlo simulations Hauk and Wacziarg (2004) show that in the estimation of a transformed version of the Solow model the greater speed of convergence reported by the fixed-effects and the Arellano

[9] Table 1 reports data on 11 countries that were not included in Forbe´s sample. This countries are Algeria, Iran, Israel, Jordan, Ghana, Mauritius, South Africa, Uganda, Honduras, Jamaica and Taiwan. However, Table 1 does not report data on Bulgaria because this country is not included in Castello and Domenech (2002) data set.

and Bond GMM estimators is due to the greater measurement error bias present in these estimators. In general, allowing for measurement error and country specific effects correlated with the explanatory variables the authors find that the OLS estimator applied to variables averaged over the period performs better in terms of bias than any other estimator commonly used in growth regressions.

Table 1- Income Gini coefficients for 55 countries

Country	1965	1970	1975	1980	1985	1990	1995	Mean	St.dv.
Middle East and North Africa									
Algeria	-	-	-	-	-	0.453	0.419	0.436	0.024
Tunisia	-	-	0.506	0.496	0.496	0.468	-	0.492	0.016
Iran	-	0.521	0.489	-	-	-	-	0.505	0.022
Israel	-	-	-	-	-	0.309	0.305	0.307	0.003
Jordan	-	-	-	-	-	0.427	0.473	0.450	0.032
Sub-Saharan Africa									
Ghana	-	-	-	-	-	0.359	0.340	0.350	0.014
Mauritius	-	-	-	-	-	0.462	0.433	0.448	0.021
South Africa	-	-	-	-	-	0.630	0.623	0.627	0.005
Uganda	-	-	-	-	-	0.396	0.474	0.435	0.055
Latin America and the Caribbean									
Costa Rica	-	-	0.444	0.450	0.470	0.461	-	0.456	0.012
Dominican R.	-	-	-	0.450	0.433	0.505	0.490	0.470	0.035
Honduras	-	-	-	-	-	0.540	0.540	0.540	0.000
Jamaica	-	-	-	-	-	0.484	0.445	0.465	0.027
Mexico	0.555	0.577	0.579	0.500	0.506	0.550	0.570	0.548	0.033
Trinidad & Tobago	-	-	0.510	0.461	0.417	-	-	0.463	0.046
Brazil	-	0.576	0.619	0.578	0.618	0.596	0.637	0.604	0.025
Chile	-	0.456	0.460	0.532	-	0.547	0.556	0.510	0.048
Colombia	-	0.520	0.460	0.545	-	0.512	0.513	0.510	0.031
Peru	-	-	-	-	0.493	0.494	0.515	0.501	0.012
Venezuela	-	-	0.477	0.394	0.428	0.538	-	0.459	0.063
East Asia and the Pacific									
Hong Kong	-	-	0.398	0.373	0.452	0.420	0.450	0.419	0.034
Indonesia	0.399	0.373	-	422	0.390	0.397	0.383	0.394	0.017
Korea	0.343	0.333	0.360	0.386	0.345	0.336	0.382	0.355	0.022
Malaysia	-	0.500	0.518	0.510	0.480	0.484	-	0.498	0.016
Philippines	-	-	-	-	0.461	0.457	0.450	0.456	0.006
Singapore	-	-	0.410	0.407	0.420	0.390	0.378	0.401	0.017
Taiwan	0.322	0.294	0.312	0.280	0.292	0.301	0.308	0.301	0.014
Thailand	0.413	0.426	0.417	-	0.431	0.488	0.515	0.448	0.042
South Asia									
Bangladesh	0.373	0.342	0.360	0.352	0.360	0.355	0.349	0.356	0.010
India	0.377	0.370	0.358	0.387	0.381	0.363	0.386	0.375	0.011
Pakistan	0.387	0.365	0.381	0.389	0.390	0.380	0.378	0.381	0.009
Sri Lanka	0.470	0.377	0.353	0.420	0.453	0.367	0.410	0.407	0.044
Advanced Countries									
Canada	0.316	0.323	0.316	0.310	0.328	0.276	0.277	0.307	0.022
United States	0.346	0.341	0.344	0.352	0.373	0.378	0.379	0.359	0.017
Japan	0.348	0.355	0.344	0.334	0.359	0.350	-	0.348	0.009
Belgium	-	-	-	0.283	0.262	0.266	0.269	0.270	0.009
Denmark	-	-	-	0.310	0.310	0.332	0.332	0.321	0.013
Finland	-	0.318	0.270	0.309	0.308	0.262	0.261	0.288	0.026
France	0.470	0.440	0.430	0.349	0.349	-	-	0.408	0.055
Germany	0.281	0.336	0.306	0.321	0.322	0.260	0.274	0.300	0.029
Greece	-	-	-	-	0.399	0.418	-	0.409	0.013
Ireland	-	-	0.387	0.357	-	-	-	0.372	0.021
Italy	-	0.380	0.390	0.343	0.332	0.327	0.322	0.349	0.029
Netherlands	-	-	0.286	0.281	0.291	0.296	0.294	0.290	0.006
Norway	0.375	0.360	0.375	0.312	0.314	0.331	0.333	0.343	0.027
Portugal	-	-	0.406	0.368	-	0.368	0.356	0.374	0.022
Spain	-	-	0.371	0.334	0.318	0.325	0.350	0.340	0.021
Sweden	-	0.334	0.273	0.324	0.312	0.325	0.324	0.316	0.022
Turkey	-	0.560	0.510	-	-	0.441	0.415	0.481	0.066
United Kingdom	0.243	0.251	0.233	0.249	0.271	0.323	0.324	0.271	0.038
Australia	-	-	-	0.393	0.376	0.412	0.444	0.407	0.028
New Zealand	-	-	0.300	0.348	0.358	0.402	-	0.352	0.042
Transitional Economies									
China	-	-	-	0.320	0.314	0.346	0.378	0.340	0.029
Hungary	0.259	0.229	0.228	0.215	0.210	0.233	0.279	0.236	0.025
Poland	-	-	-	0.249	0.253	0.262	0.331	0.274	0.038
Mean	0.369	0.395	0.393	0.375	0.377	0.400	0.401	0.403	0.025
Std. dv.	0.079	0.097	0.093	0.085	0.083	0.095	0.097	0.088	0.015
Countries	17	26	36	40	40	51	44	55	55

Note- Gini coefficients are taken from the latest available data closest to the corresponding period. A value of 0.066 has been added to the Gini coefficients based on expenditure. Source: Deininger and Squire (1996) and UNU/WIDER-UNDP World Income Inequality Data Base (2000) .

Table 2 provides the results of the cross-section and pool estimations where no fixed effects are taking into account (equation (1)). In order to increase the number of observations, the dependent variable in the cross-section regressions (Columns (1)-(4)) is the average growth rate over the period 1975-2000.[10] The explanatory variables include the naturally log of per capita income (lny), the income Gini coefficient ($Gini^y$), the human capital Gini coefficient ($Gini^h$), the average years of secondary schooling in the female population ($Educf$), the average years of secondary schooling in the male population ($Educm$) and the current price level of investment (pi). All the explanatory variables are measured in 1975.

Column (1) shows the results obtained in the literature that analyses the effects of inequality on growth estimating cross-section regressions. In line with these studies, the coefficient of the income Gini index is negative and statistically significant, suggesting a negative effect on growth from higher initial income inequality. However, as pointed out by Castello and Domenech (2002), this result is not robust to the inclusion of regional dummies. When we include dummies for Latin America and the East Asian regions, as it is displayed in column (2), the coefficient of the income Gini index stops being statistically significant. On the contrary, even controlling for regional dummies the coefficient of the human capital Gini index is negative and statistically significant at the standard levels (column (3)). When both inequality indicators are included in the equation neither the coefficient of the income Gini index nor the coefficient of the human capital Gini index are statistically significant. This may be due to the fact that we are including too many controls in a sample with very few countries.

We can increase the number of observation by extending the data in their temporal dimension. Columns (5) to (7) show the results of the OLS pool regressions for the whole period 1965-2000. These regressions also include time dummies to diminish the possible incidence of business cycles in the estimated coefficients. The results are quite similar to the ones obtained in the cross-section regressions. On the one hand, the coefficient of the income Gini index is negative but not statistically significant. On the other hand, the relationship between human capital inequality and economic growth is negative with a coefficient that is statistically significant in all cases. With regard to the other controls, one surprising result could be that whereas male education has a positive effect on the growth rate, the coefficient of the female education is negative and statistically significant. The explanation given in the literature for the negative coefficient is that lower levels of female education is an indication of backwardness and, therefore, a greater potential growth through the convergence process. The coefficient of the investment price is negative, as expected, and also statistically significant.

[10] We choose 1975 as the starting period because it is the closest period to 1965 with a greater number of observations.

Table 2- Cross-section and pool regressions

	Cross-Section				Pool		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.050**	0.050***	0.081**	0.082**	0.048***	0.084***	0.085***
	(0.024)	(0.016)	(0.029)	(0.032)	(0.017)	(0.026)	(0.026)
lny	-0.001	-0.003	-0.006**	-0.006	-0.001	-0.005*	-0.004*
	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)
$Gini^y$	-0.036**	-0.018		0.008	-0.028		-0.008
	(0.016)	(0.019)		(0.031)	(0.019)		(0.018)
$Gini^h$			-0.022*	-0.024		-0.033**	-0.031**
			(0.012)	(0.017)		(0.013)	(0.013)
Educf	-0.013**	0.004	0.001	0.001	-0.005	-0.008**	-0.008**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Educm	0.015**	-0.003	0.001	0.001	0.006**	0.009***	0.009**
	(0.006)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
pi	-0.015*	-0.002	-0.002	-0.002	-0.010*	-0.009*	-0.010*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
laam		-0.007	-0.011**	-0.012	-0.003	-0.007*	-0.006
		(0.006)	(0.004)	(0.008)	(0.005)	(0.004)	(0.005)
asiae		0.023***	0.020***	0.020***	0.018***	0.015***	0.016***
		(0.004)	(0.005)	(0.06)	(0.004)	(0.004)	(0.004)
Time dummies					yes	yes	yes
R^2	0.332	0.646	0.686	0.687	0.255	0.282	0.282
Countries	36	36	36	36	55	55	55
Obs	36	36	36	36	250	250	250
Period	1975-2000	1975-2000	1975-2000	1975-2000	1965-2000	1965-2000	1965-2000

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. Dependent variable: Annual per capita growth rate. Independent variables: ln of per capita income (*lny*), income Gini coefficient ($Gini^y$), human capital Gini coeficient ($Gini^h$), average years of secondary schooling in the female population (*Educf*), average years of secondary schooling in the male population (*Educm*), the current price level of investment (*pi*) and regional dummies for Latin American (*laam*) and East Asian countries (*asiae*). Time dummies for the years 1970, 1975, 1980, 1985, 1990 and 1995 are included in columns (5)-(7).

On the whole, the cross-section and pool regressions suggest that the negative coefficient of income inequality on economic growth, found in previous studies, stops being statistically significant when regional dummies are included in the equation whereas, even controlling for average schooling variables and regional dummies, the inequality in the distribution of education seems to have an important role in determining the growth rates of the economies.

As we mentioned above the coefficients obtained in these estimations may be biased due to the omission of relevant explanatory variables that are difficult to measure. If these variables are important determinants of the income growth rates and are related to the explanatory variables the coefficients displayed in Table 2 are biased. To solve this problem we can estimate a panel data model that takes into account the three components of the error term enumerated in equation (2).

In the first place we treat the country-specific effects as random. The results of the random effect model are shown in Columns (1)-(3) of Table 3. The results concerning the inequality variables in the pool estimations almost hold under the random effects model. The coefficients of the Gini indexes are both negative although only the coefficient of the human capital Gini index is statistically significant. Columns (4)-(6) display the results when we estimate the model assuming that the country-specific effects are fixed. Surprisingly, removing all cross-country variation makes the coefficient of the income Gini index become positive and statistically significant. However, the coefficient of the human capital Gini index remains negative and statistically significant even ruling out cross-country variation. The validity of any of these results depend on the assumption we can make on the error term, if the country-specific effects are random the GLS estimator is consistent and efficient whereas the within estimator is consistent but not efficient. On the contrary, if the country-specific effects are not random and are related to the explanatory variables the within estimator is consistent whereas the GLS estimator is not. In order to discriminate between both models we can apply a Haussman test. Under the null hypothesis of random effects both estimators are consistent and there should not be a systematic difference in coefficients. The *chi* squared values for the tests are 43.93 (Columns (1) and (4)), 28.64 (Columns (2) and (5)) and 42.88 (Columns (3) and (6)), with probability 0.000, 0.003 and 0.000 respectively, which implies that the country-specific effects should not be treated as random.

The fixed effect model suggest a different relation between income and education inequality with the economic growth rates. Whereas income inequality has a positive relationship with economic growth rates, greater education inequality is related to lower growth rates within a country. However, given that the estimated model is a dynamic model it is obvious that the country-specific effect is at least related to the lagged income explanatory variable. In addition, the presence of a lagged explanatory variable makes the assumption of strict exogeneity difficult to hold. Therefore, it means that none of the previous estimators is consistent.

To achieve a consistent an efficient estimator we may apply the GMM estimator of Arellano and Bond (1991). Moreover, this technique allows us to treat some of the explanatory variables as endogenous. On the one hand, not only inequality affects economic growth but also economic growth may affect inequality. Kuznets (1955) suggests that inequality changes with the process of development, increasing in the first stages of development and reducing at later stages, implying an inverted U-shaped relationship between inequality and income. On the other hand, higher growth rates imply more development, which may induce to higher education levels. In order to account for these feedbacks we treat inequality variables and education variables as endogenous.

Table 3- Random and Fixed effects

	Random effects			Fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.069***	0.112***	0.118***	0.371***	0.460***	0.433***
	(0.025)	(0.028)	(0.030)	(0.064)	(0.069)	(0.068)
lny	-0.005	-0.009***	-0.009***	-0.043***	-0.046***	-0.048***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)
$Gini^y$	-0.021		-0.009	0.102**		0.102***
	(0.021)		(0.021)	(0.039)		(0.038)
$Gini^h$		-0.043***	-0.042***		-0.062**	-0.062**
		(0.013)	(0.014)		(0.027)	(0.026)
Educf	-0.006	-0.011**	-0.010**	0.002	0.001	0.001
	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.006)
Educm	0.010**	0.014***	0.013***	0.004	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
pi	-0.017***	-0.017***	-0.017***	-0.017**	-0.015**	-0.015**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Time dummies	yes	yes	yes	yes	yes	yes
R^2	0.146	0.180	0.181	0.257	0.251	0.279
Countries	55	55	55	55	55	55
Obs	250	250	250	250	250	250
Period	1965-2000	1965-2000	1965-2000	1965-2000	1965-2000	1965-2000

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. See Table 2 for definition of variables. R^2 is overall for random effects and within for fixed effects. Time dummies for the years 1965, 1970, 1975, 1980, 1985 and 1990 are included in columns (1)-(6).

Table 4 reports the results of the GMM estimators treating $Gini^y$, $Gini^h$, *Educf* and *Educm* as endogenous.[11] Columns (1)-(3) display the results of the first difference GMM estimator also used by Forbes (2000). The results show a negative and statistically significant coefficients of the initial per capita income and the price of investment. With regard to the inequality variables, on the one hand, as it was the case in the fixed effects model, the income inequality coefficient is positive and statistically significant in all cases, corroborating Forbes' (2000) results. On the other hand, the coefficient of education inequality remains always negative and it is also statistically significant. Therefore, the results point out that the negative effect on growth from human capital inequality, found in Castello and Domenech (2002), is not due to omitted variables bias.

Nevertheless, Bond et al. (2001) suggest using system GMM in the estimation of growth equations since first differences GMM estimators may be biased

[11] In order to compare the estimated coefficients of equation (1) and (3) the results obtained using the GMM estimator are shown according to the transformations displayed after equation (3).

due to a problem of weak instruments. For this reason columns (4) to (6) display the results of the system GMM estimator. The results show that using the variables in differences to instrument an additional level equation changes the estimated coefficients. In particular, the coefficient of the income Gini index continues being positive although it is not statistically significant at the standard levels. In addition, the coefficient of the initial per capita income is reduced significantly and the coefficients of the average years of schooling are now statistically significant. With regard to education inequality, the human capital Gini index continues having a negative and statistically significant effect on growth.

The consistency of the first differences and system GMM estimators depends on two identifying assumptions. The first one states the absence of second order serial correlation. The second one regards with the validity of the istruments. We examine the first assumption testing the hypothesis that the differenced error term is not second-order serially correlated. The second assumption is analysed through the Sargan test of over-identifying restrictions, which test the null hypothesis of validity of the instruments. The p-values shown in Table 4 give support to the identifying assumptions since in all cases we do not reject the null hypothesis.

Overall, the results suggest that the effect of income inequality on the growth rates depends to some extent on the technique used to estimate the model. Whereas cross-section and pool regressions show a negative relationship between income inequality and growth, controlling for fixed effects displays a positive effect on the growth rate within a country from an increase in income inequality in that country. However, the negative relationship between human capital inequality and economic growth appears to be extremely robust to the estimation of different models. In particular, the negative effect on growth from human capital inequality is found not only in cross-section regressions but also in the estimation of a dynamic panel data model that controls for country-specific effects.

4 Human capital and economic growth: broader sample

One of the main criticisms to Forbes' (2000) study is that the results may suffer from sample selection bias due to the restrictive number of countries for which there are data on income inequality. In addition to measurement error problem, one of the main shortcomings with income inequality data measures is that the least developed countries are underrepresented. For example, in Forbes' sample almost half of the countries are OECD countries and there are no data for any Sub-Saharan African country. Although we have extended Forbes' sample and, therefore, improved in some sense that shortcoming, some regions such us

Sub-Saharan African countries are still underrepresented.[12]

Table 4- Generalized Method of Moments

	Differences			System		
	(1)	(2)	(3)	(4)	(5)	(6)
lny	-0.054***	-0.061***	-0.068***	-0.003***	-0.008***	-0.007***
	(0.005)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)
$Gini^y$	0.203***		0.164***	0.007		0.061
	(0.059)		(0.051)	(0.041)		(0.039)
$Gini^h$		-0.076*	-0.071**		-0.036	-0.051***
		(0.039)	(0.034)		(0.023)	(0.018)
Educf	0.003	0.007	-0.001	-0.010	-0.013**	-0.017**
	(0.013)	(0.011)	(0.011)	(0.007)	(0.007)	(0.007)
Educm	0.007	0.003	0.006	0.015*	0.018**	0.020***
	(0.014)	(0.011)	(0.012)	(0.007)	(0.007)	(0.007)
pi	-0.021**	-0.023**	-0.014*	-0.014	-0.017*	-0.015
	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)	(0.010)
Time dummies	yes	yes	yes	yes	yes	yes
Countries	55	55	55	55	55	55
Obs.	189	189	189	248	248	248
Period	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000	1970-2000
2^{nd} order	-1.48	-1.80	-1.53	-1.04	-1.18	-0.95
cor. test	p=0.139	p=0.071	p=0.127	p=0.297	p=0.238	p=0.344
Sargan test	$\chi^2_{(98)}$ 47.16	$\chi^2_{(98)}$ 42.36	$\chi^2_{(118)}$ 43.66	$\chi^2_{(120)}$ 38.47	$\chi^2_{(120)}$ 40.13	$\chi^2_{(146)}$ 41.79
p-value	1.00	1.00	1.00	1.00	1.00	1.00

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. See Table 2 for definition of variables. Columns (4)-(6) include a constant and regional dummies for Latin america and East Asian countries. Time dummies for the years 1975-2000 are included in columns (1)-(3) and for the years 1970-2000 in columns (4)-(6). The instruments used for the first difference GMM estimator are the levels of the per capita income, Gini coefficients and schooling variables lagged two periods and all further lags, the price of investment lagged one period and the time dummies. In addition to these variables the system GMM also uses as instruments for the level equations the first difference of the per capita income, Gini coefficients and schooling variables lagged one period.

We can partially solve this problem since the human capital inequality data set does not suffer from such restriction. The human capital inequality data set includes a broad number of countries and all geographical regions are represented. There are data for 12 Middle East and North African countries, 29 Sub-Saharan African countries, 23 Latin America and Caribbean countries, 10 countries from East Asia and the Pacific region, 7 South Asian countries, 23

[12] In the extended sample used in this study there are data for four Sub-Saharan African countries, each of them with data available only in 1990 and in 1995.

Advanced Countries and 4 Transitional Economies. The availability of data for a large amount of countries will avoid the sample selection bias that can be present in Forbes' results.

Due to the fact that there are very few observations on income inequality variables, Perotti (1996) and Forbes (2000) choose a parsimonious specification to analyse the relationship between income inequality and economic growth in which the set of explanatory variables is quite reduced. In order to estimate a more appropriate model that controls for a greater number of variables we need to increase the number of observations in the sample. We have several possibilities. One way is to include additional income inequality data that are not classified as high quality. However, some regions such as Sub-Saharan Africa will continue being underrepresented and, in addition, it will increase the measurement error problem. An alternative way that does not suffer from such shortcomings is to restrict the analysis to the relationship between human capital inequality and economic growth. Restricting the analysis to this relation not only implies increasing the sample up to 89 countries but also to broaden the available period for most of the existing countries. The extension of the data set will also enable us to use a different and more appropriate specification that extends the set of explanatory variables in line with Barro's (2000) equations.

Although in the recent years the endogenous growth models have contributed in explaining the determinants of the long-run growth rates of the economies, the empirical literature has included the convergence property derived from the neoclassical growth model in the estimated equations. According to the neoclassical growth model, on the one hand, conditioning for the variables that determine the steady-state, the law of diminishing returns in the accumulation of physical and human capital imply a lower growth rate the greater the level of development of the country. On the other hand, the model predicts that a change in the determinants of the steady state only affect the long run level of per capital income, implying that these factors may influence the transitional dynamics but not the long run growth rate.

The empirical analyses usually estimate a broaden version of the neoclassical growth model that includes the convergence property as well as other variables that determine the steady state. In this line, the model estimated in this section will control for initial conditions variables and some variables, chosen by the government or private agents, which characterize the steady state conditions. The variables that account for the initial conditions are the level of per capita income ($ln\mathrm{y}$) as well as its squared ($ln\mathrm{y}^2$).[13] The initial stock of human capital is proxied by the average years of male secondary and higher schooling of population aged 25 years and over ($\mathrm{schoolm}_{i,t-\tau}$).[14] The determinants of the steady state include some variables that answer for government policies and other that refer to optimal decisions by private agents. These variables include the ratio of real government consumption expenditure net of spending on defense and on

[13] The squared of per capita income is included because the evidence suggests that conditional convergence is not linear.

[14] Evidence also suggests that higher male levels of education accounts more for growth than primary and female education.

education to real GDP ($G/GDP_{i,t-\tau}$); the number of assassinations per million population per year ($assassp_{i,t-\tau}$); the terms of trade shock, measured as the growth rate of export prices minus growth rate of import prices ($TOT_{i,t-\tau}$); the log of the ratio of real domestic investment (private plus public) to real GDP ($s^k \equiv I/GDP_{i,t-\tau}$) and the log of total fertility rate ($FERT_{i,t-\tau}$). The equation to be estimated also includes regional dummies for Latin America, East Asian and South African countries since their patterns of growth have been different. For example, the growth rates of South African and Latin American countries have been relatively low whereas in East Asia region has been relatively high.

Nevertheless, this general specification includes the investment rate as an explanatory variable and most of the theoretical models show a negative effect from wealth inequality on economic growth through a discouraging effect on the investment rates. Hence, given that the investment rate is an endogenous variable in the model, we show three different regressions for every econometric model. The first one includes the investment rate in the set of explanatory variables. Therefore, the coefficient of the human capital Gini index in this equation collects any other effect from inequality on growth different from physical capital accumulation, for example, through a reduction in the rate of human capital accumulation. The second equation eliminates the physical capital investment rate from the set of explanatory variables, which should increase the coefficient of the human capital Gini index. Finally, in order to analyse the direct effect from human capital inequality on the investment rate, in the last equation the physical capital investment rate is the dependent variable.

Table 5 shows the results for the OLS cross-section and pool regressions. The results display a non-linear convergence rate, with a negative relation between initial per capita income and economic growth only from a given level of development. Initial secondary and tertiary male education have a positive effect on subsequent economic growth rates. A higher fertility rate has a negative impact on the growth rates. The explanation is that, on the one hand, a higher fertility rate increases the rate of population growth and, on the other hand, it deviates resources from the production of goods to the rear of children. Whereas physical capital investment rate has a positive effect on economic growth rates, non productive government spending has a negative one. The measure of political instability, ASSAS, is negatively related to economic growth and an improvement in the terms of trade, measured as the ratio of export to import prices, has a positive effect on growth. Finally, the coefficients of the human capital Gini index suggest a negative effect on growth mainly through a discouraging effect on the investment rate, since it is in the equation of the physical capital investment rate where the coefficient of the education inequality indicator is statistically significant.

As it was mentioned above, cross-section and pool estimations may be inconsistent due to omitted variable bias. In order to obtain consistent estimators, we estimate the dynamic panel data model using the first differences and the system GMM estimators. In relation to the equation where the physical capital investment rate is the dependent variable we use the fixed effects and random effects estimators.

Table 5- Cross-Section and Pool Regressions

	OLS Cross-Section			OLS POOL		
	dlny	*dlny*	lns_k	*dlny*	*dlny*	lns_k
	(1)	(2)	(3)	(4)	(5)	(6)
constant	-0.146*	-0.169*	-3.719	-0.306***	-0.361***	-4.080
	(0.080)	(0.093)	(7.128)	(0.110)	(0.114)	(3.669)
lny	0.053**	0.072***	1.851	0.095***	0.118***	1.700*
	(0.020)	(0.022)	(1.718)	(0.027)	(0.028)	(0.876)
lny^2	-0.004***	-0.005***	-0.117	-0.007***	-0.008***	-0.096*
	(0.001)	(0.001)	(0.104)	(0.002)	(0.002)	(0.052)
$school_m$	0.001	0.002	0.010	0.002*	0.002*	-0.007
	(0.001)	(0.001)	(0.031)	(0.001)	(0.001)	(0.022)
$Gini^h$	0.001	-0.012	-0.984**	0.005	-0.007	-0.920***
	(0.009)	(0.010)	(0.422)	(0.009)	(0.008)	(0.196)
G/GDP	-0.073***	-0.097***	-1.578	-0.047*	-0.067***	-1.468**
	(0.023)	(0.019)	(0.9979	(0.025)	(0.025)	(0.654)
ASSAS	-0.009	-0.014	-0.416	-0.031*	-0.036**	-0.369**
	(0.018)	(0.014)	(0.614)	(0.016)	(0.015)	(0.179)
$\ln s_k$	0.013***			0.014***		
	(0.004)			(0.003)		
lnFERT	-0.017***	-0.018**	0.009	-0.020***	-0.019***	0.067
	(0.006)	(0.007)	(0.250)	(0.005)	(0.006)	(0.105)
TOT	0.057	0.065	0.580	0.056**	0.060**	0.300
	(0.066)	(0.075)	(2.874)	(0.026)	(0.028)	(0.544)
laam	-0.003	-0.008*	-0.337**	-0.005	-0.010***	-0.361***
	(0.003)	(0.004)	(0.148)	(0.004)	(0.004)	(0.064)
safrica	-0.005	-0.009**	-0.305*	-0.007	-0.011**	-0.312***
	(0.004)	(0.004)	(0.172)	(0.005)	(0.005)	(0.095)
asiae	0.005	0.007	0.100	0.000	0.001	0.022
	(0.004)	(0.004)	(0.152)	(0.004)	(0.004)	(0.080)
Time dummies				yes	yes	yes
R^2	0.667	0.594	0.504	0.358	0.300	0.500
Countries	81	81	81	89	89	89
Obs	81	81	81	385	385	385
Period	1960-1985	1960-1985	1960-1985	1960-1985	1960-1985	1960-1985

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. See Table 2 for definition of variables. R^2 is overall for random effects and within for fixed effects. Time dummies for the years 1965, 1970, 1975, 1980 and 1985 are included in columns (4)-(6).

Table 6 reports the results of the model controlling for fixed effects. With reference to the dynamic panel data model where the dependent variable is the growth rate of per capita income, some results differ if the model is estimated taking first differences (DIF-GMM) or, if in addition to estimate a first difference equation, we also estimate a level equation using variables in differences as instruments (SYS-GMM). Nevertheless, there are some coefficients that are statistically significant in both cases such as the coefficients of the investment rate, the human capital Gini index and the number of assassinations. Since the GMM estimator faces up the problem of endogeneity by using lagged variables as instruments, the positive and statistically significant coefficient of the physical capital investment rate suggest that the encouraging effect of investment on growth, also obtained in the previous regressions, was not due to reverse causation. The results also suggest that an increase in the number of assassinations or an increase in the inequality in the distribution of education has a discouraging effect on the growth rates.

The results of the equation where the investment rate is the dependent variable are shown in Columns (5) and (6) of Table 6. Since it is not a dynamic equation we use random and fixed effects estimators. However, the $\chi^2_{(12)}$ for the Hausman test (18.28) with probability 0.107 points out that the effects should be treated as random. The results in column (5) suggest that human capital inequality join with government spending and assassinations per year are the main variables that have had a strong and negative influence on the investment rates.

Overall, we may conclude that whereas the negative effect of human capital inequality on the physical investment rate holds in all specifications and survives the test of fixed effects, the direct influence of education inequality on growth is most of the time but not always statistically significant. However, in these estimations we have been mainly testing the influence of education inequality on growth through the physical capital investment rate. Although we have proved that the effect of education inequality on the physical capital investment is robust to many specifications and, therefore, should not be undervalued, there are other channels through which education inequality may influence the growth rates. One of these channels, modelized by De la Croix and Doepke (2003), analyses the effects of inequality on growth through the fertility decisions. In this model poor parents decide to have more children and provide less education for them whereas rich parents decision are characterized by lower and more educated children. This implies that the larger the pool of poor people the greater the weigh of uneducated individuals in the following generation and the lower the human capital investment and the growth rates in the economy.

In all specifications estimated we have observed that whereas the coefficient of the fertility rate is not statistically significant in the physical capital investment equation, the fertility rate is one of the main determinants of growth with a negative and statistically significant coefficient in almost all equations where per capita growth rate is the dependent variable. On the other hand, there is a strong relationship between human capital inequality and the fertility rates. Figure 1 plots the human capital Gini coefficient in 1960 against the average fertility rates during the period 1960-1985.

Table 6- Panel data Model

	DIF-GMM		SYS-GMM		RE	FE
	dlny	*dlny*	*dlny*	*dlny*	lns^k	lns^k
	(1)	(2)	(3)	(4)	(5)	(6)
constant			-0.106	-0.347	0.056	4.687
			(0.280)	(0.282)	(2.361)	(3.137)
lny	-0.149	-0.130	0.055***	0.131***	0.799	-0.202
	(0.261)	(0.195)	(0.015)	(0.028)	(0.572)	(0.730)
lny^2	0.005	0.004	-0.005	-0.009**	-0.043	0.009
	(0.005)	(0.006)	(0.004)	(0.004)	(0.035)	(0.044)
$school_m$	-0.004	-0.003	0.004	0.003	-0.019	-0.059
	(0.006)	(0.006)	(0.003)	(0.003)	(0.041)	(0.049)
$Gini^h$	-0.144**	-0.194***	-0.025	-0.073***	-1.059***	-1.488***
	(0.064)	(0.063)	(0.022)	(0.024)	(0.228)	(0.436)
G/GDP	0.055	0.059	-0.101*	-0.102*	-1.172**	-0.741
	(0.094)	(0.099)	(0.052)	(0.058)	(0.524)	(0.633)
ASSAS	-0.086***	-0.086***	-0.023	-0.035**	-0.350***	-0.359***
	(0.013)	(0.011)	(0.019)	(0.015)	(0.117)	(0.119)
$\ln s_k$	0.028***		0.026***			
	(0.007)		(0.007)			
lnFERT	-0.042**	-0.044**	-0.017	-0.011	-0.104	-0.102
	(0.019)	(0.019)	(0.010)	(0.013)	(0.123)	(0.144)
TOT	0.044	0.046	0.044	0.052	0.301	0.276
	(0.035)	(0.036)	(0.037)	(0.039)	(0.243)	(0.243)
Time dummies	yes	yes	yes	yes	yes	yes
R^2					0.430	0.122
Countries	87	87	89	89	89	89
Obs.	293	293	385	385	385	385
Period	1965-1985	1965-1985	1965-1985	1965-1985	1960-1985	1960-1985
2^{nd} order	-0.20	-0.35	-0.15	-0.42		
corr. test	p=0.845	p=0.727	p=0.885	p=0.674		
Sargan test	$\chi^2_{(81)}$ 63.93	$\chi^2_{(72)}$ 67.62	$\chi^2_{(114)}$ 76.13	$\chi^2_{(101)}$ 79.07		
p-value	0.869	0.624	0.998	0.948		

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. Time dummies for the years 1970-1985 in columns (1) to (4) and for the years 1965-1985 in columns (5) and (6). R^2 is overall for random effects and within for fixed effects.

The picture clearly shows that those countries with a greater inequality in the distribution of education in 1960 are those in which women, on average, have had a greater number of children.[15] Therefore, given that human capital

[15] The coefficient of the human capital Gini index in the linear regression is 5.448 with a robust standard error equal to 0.304. The number of observation is 96 and the R^2=0.692.

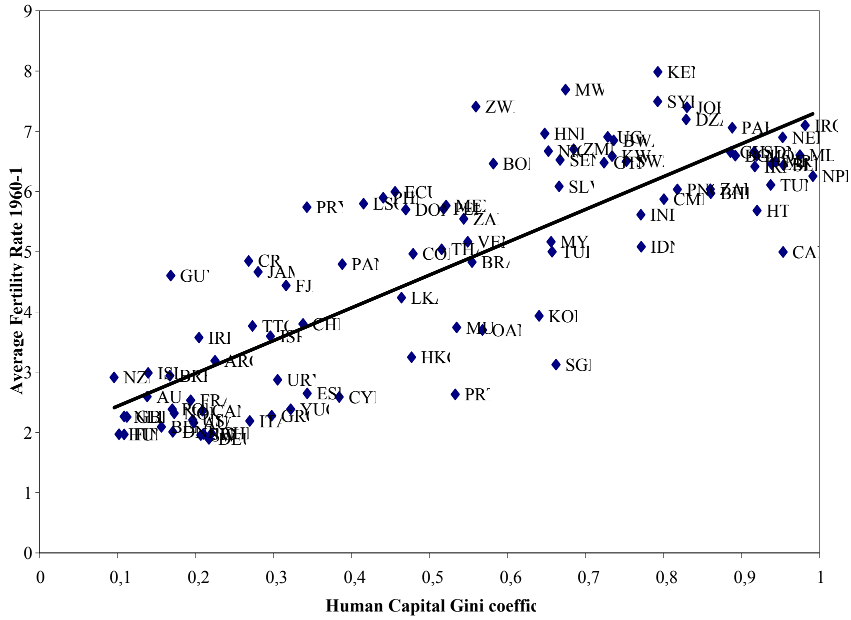

Figure 1: Human Capital Inequality and Average Fertility Rates

inequality may affect growth not only through a discouraging effect on physical capital investment rate but also through a positive correlation with the fertility rate, in Table 7 the investment and fertility rates are excluded from the set of explanatory variables. As a result, the coefficient of the human capital Gini index in all estimated equations is negative and statistical significant. Column (1) of Table 7 displays the long-term results in the OLS cross-section estimation where, controlling for other variables, the coefficient of the human capital Gini index collects the effect of an increase in human capital inequality in 1960 over the average growth rate in the subsequent 25 years. Under the presence of country-specific effects the coefficients of the OLS estimations are inconsistent, for this reason column (3) shows the results of the fixed effect model, which also reports a negative and statistically significant coefficient for the human capital Gini index. However, the presence of the lagged dependent variable as an explanatory variable makes the fixed effect model also inconsistent. In addition, most of the explanatory variables should be treated as endogenous since their coefficients may indicate a problem of reverse causation. Columns (4) and (5) display the results of the first differences and system generalized

Since the initial human capital Gini coefficent may be picking up the level of development of the country, we also run a regression controlling for the initial income per capita. The coefficient of the human capital Gini index in this regression continues being positive and statistically significant with a value of 3.402 and a robust standard error equal to 0.590, the R^2 is 0.729.

method of moments estimators. The results show that the coefficient of the human capital Gini index continues being negative and statistically significant.

Given that removing the fertility rates from the set of explanatory variables makes the coefficient of the human capital Gini index negative and statistically significant in all equations, the results point out that part of the negative effect that human capital inequality exerts on the growth rates may be driven by the fertility channel.

Once we remove the investment and the fertility rates, we can compute the quantitative effects of an increase in human capital inequality on the growth rate. For example, the system GMM reports a coefficient of the human capital Gini index about 0.086, which implies that a reduction in the human capital inequality by 0.20 points would increase the average annual growth rate over the following 5 years in about 1.72% points.[16]

5 Conclusions

Most of the cross-sectional studies that have analysed the relationship between inequality and growth have found a negative effect from inequality in the distribution of income on the economic growth rates. However, the negative relationship between income inequality and economic growth disappears when a panel data model that controls for fixed effects is estimated. Using Arellano and Bond (1991) estimator, Forbes´(2000) results suggest that in the short and medium term an increase in the level of income inequality in a country has a positive and statistically significant relationship with its subsequent economic growth rates.

With the objection that income inequality could be a poor proxy for wealth inequality as well as objections about the quality and quantity of income inequality data, Castello and Domenech (2002) also analyse the effect of human capital inequality on economic growth in cross-section regressions. They found a quite robust and negative effect from initial human capital inequality on the subsequent economic growth rates.

However, cross section estimators do not control for country specific effects and, as a result, the estimated coefficients could suffer from a problem of omitted variable bias. Being aware that this problem can be relevant, since controlling for fixed effects gives different results in the analysis of the relationship between income inequality and economic growth, the aim of this study is to investigate whether the negative relationship between human capital inequality and economic growth, found in cross-section studies, also becomes a positive one when a dynamic panel data model that controls for fixed effects is estimated.

In addition to human capital inequality, this paper also analyses the relationship between income inequality and economic growth. To address this issue, it extends the income inequality data set utilized by Forbes (2000) and also uses

[16] The standard deviation of the human capital Gini index across countries in every period is about 0.2 points.

a new generalized method of moments estimator that seems to perform better in growth regressions.

Table 7- Fertility Channel

	OLS (1)	OLS-POOL (2)	FE (3)	DIF-GMM (4)	SYS-GMM (5)
constant	-0.212**	-0.338***	0.416*		-0.306
	(0.085)	(0.115)	(0.250)		80.297)
lny	0.075***	0.101***	-0.047	-0.161	0.113***
	(0.022)	(0.029)	(0.058)	(0.487)	(0.026)
lny^2	-0.005***	-0.007***	0.000	0.006	-0.008*
	(0.001)	(0.002)	(0.003)	(0.007)	(0.004)
$school_m$	0.002*	0.003**	0.004	0.001	0.004
	(0.001)	(0.001)	(0.004)	(0.006)	(0.004)
$Gini^h$	-0.025***	-0.018**	-0.062*	-0.174**	-0.086***
	(0.008)	(0.009)	(0.035)	(0.074)	(0.024)
G/GDP	-0.101***	-0.056**	0.043	0.112	-0.086
	(0.020)	(0.025)	(0.051)	(0.093)	(0.064)
ASSAS	-0.014	-0.035***	-0.050***	-0.072***	-0.034**
	(0.014)	(0.013)	(0.009)	(0.009)	(0.014)
TOT	0.036	0.053*	0.052***	0.044	0.052
	(0.074)	(0.028)	(0.019)	(0.035)	(0.039)
laam	-0.013***	-0.014***			-0.020*
	(0.003)	(0.003)			(0.011)
safrica	-0.011***	-0.012***			0.003
	(0.004)	(0.004)			(0.014)
asiae	0.007	0.002			0.021*
	(0.005)	(0.004)			(0.012)
Time dummies		yes	yes	yes	yes
R^2	0.553	0.280	0.321		
Countries	81	89	89	87	89
Obs.	81	385	385	293	385
Period	1960-1985	1960-1985	1960-1985	1965-1985	1965-1985
2^{nd} order corr. test				-0.27 p=0.789	-0.37 p=0.709
Sargan test				$\chi^2_{(63)}$ 61.45	$\chi^2_{(88)}$ 80.68
p-value				0.532	0.697

Note- Robust standard errors in parenthesis. *** 1 per cent significance level, ** 5 per cent significance level, * 10 per cent significance level. Time dummies for the years 1965-1980 in columns (2) and (3), for the years 1970-1985 in column (4) and for the years 1965-1985 in column (5) are included.

The main findings of the paper are as follows. In line with Forbes' (2000), this study finds a positive relationship between income inequality and economic growth when the dynamic equation is estimated with the first-differences GMM estimator. However, the statistically significant correlation disappears when a more appropriate generalized method of moment estimator is used.

With reference to human capital inequality, using the first differences and the system generalized method of moments estimators the paper does not find evidence of a positive relation between human capital inequality and economic growth in the estimation of a dynamic panel data model that controls for fixed effects. All the contrary, the results suggest that human capital inequality is related negatively to subsequent growth rates. This result holds not only in long-term relations across-countries, as analyzed in cross-section regressions, but also in short term periods within a country, as analyzed by the fixed effects model. In addition the paper provides evidence of two ways through which human capital inequality may affect growth. The first one is through a discouraging effect from human capital inequality on the physical capital investment rates and the second one involves a strong positive association between human capital inequality and fertility decisions.

On the whole, whereas the relationship between income inequality and economic growth is not robust, cross-section and fixed effects models coincide in pointing out that an increase in the inequality in the distribution of education is followed by a reduction in the per capita income growth rates. The policy implication of these results are important since they suggest that a more even distribution of opprotunities, through a wide access to education, could not only improve que quality of life of individuals but also the economic performance of countries.

.

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6 Appendix

I- Computation of the human capital Gini coefficient

The human capital Gini coefficient is computed using data on the average schooling years and the attainment levels provided by Barro and Lee (2001). The formula to compute the Gini coefficient is:

$$G^h = \frac{1}{2\overline{H}} \sum_{h=1}^{S} \sum_{l=1}^{S} |\widehat{x}_h - \widehat{x}_l| \, n_h n_l \tag{A- 1}$$

where $\overline{H}$ is the average schooling years in the total population, $\widehat{x}_h$ is cumulative average schooling years of each educational level, and n_h is the share of population aged 15 and over with the level h as the the highest educational attainment level. Expanding expression (A- 1), the Gini coefficient can be written as follows:

$$G^h = n_0 + \frac{n_1 x_2 (n_2 + n_3) + n_3 x_3 (n_1 + n_2)}{n_1 \widehat{x}_1 + n_2 \widehat{x}_2 + n_3 \widehat{x}_3} \tag{A- 2}$$

II- Data Appendix

Table A-1: Data definition and source

Variable	Definition	Source
Education inequality ($Gini^h$)	Human capital Gini coefficient	Castello and Domenech (2002)
Female education (*Educf*)	Average years of secondary schooling in the female population	Barro and Lee (2001)
Income (y)	Real GDP per capita (chain), 1996 international prices	Heston, Summers and Aten, PWT 6.1 (2002)
Income inequality ($Gini^y$)	Income Gini coefficient	Deininger and Squire (1996) and UNU/ WIDER-UNDP (2000)
Male education (*Educm*)	Average years of secondary schooling in the male population	Barro and Lee (2001)
Price of investement (*pi*)	PPP I / Exchange rate relative to US * 100	Heston, Summers and Aten, PWT 6.1 (2002)
Male and female education (*Schoolm*)	Average years of male secondary and higher schooling of population 25 years and over	Barro and Lee (2001)
Government spending (*G/GDP*)	Ratio of real government "consumption" expenditure net of spending on defense and on education to real GDP	Summers and Heston v. 5.5 (Barro and Lee (1994))
Number of assassinations (*ASSAS*)	Number of assassinations per million population per year	Banks (Barro and Lee (1994))
Terms of trade (*TOT*)	Terms of trade shock (growth rate of export prices minus growth rate of import prices)	UNCTAD (Barro and Lee (1994))
Investment rate (s^k)	Ratio of real domestic investment (private plus public) to real GDP	Heston, Summers and Aten, PWT 6.1
Fertility rate (*FERT*)	Total fertility rate	(Barro and Lee (1994))

Table A-2- Countries included in the study

Country	Data on income inequality	Country	Data on income inequality	Country	Data on income inequality
Algeria	Yes	Guatemala	No	Pakistan	Yes
Benin	No	Haiti	No	Philippines	Yes
Botswana	No	Honduras	Yes	Singapore	Yes
Cameroon	No	Jamaica	Yes	Sri Lanka	Yes
Central Africa Rep.	No	Mexico	Yes	Syria	No
Congo	No	Nicaragua	No	Taiwan	Yes
Egypt	No	Panama	No	Thailand	Yes
Gambia	No	Trinidad & Tobago	Yes	Austria	No
Ghana	Yes	United States	Yes	Belgium	Yes
Kenya	No	Argentina	No	Cyprus	No
Lesotho	No	Bolivia	No	Denmark	Yes
Malawi	No	Brazil	Yes	Finland	Yes
Mali	No	Chile	Yes	France	Yes
Mauritania	No	Colombia	Yes	Germany	Yes
Mauritius	Yes	Ecuador	No	Greece	Yes
Mozambique	No	Guyana	No	Hungary	Yes
Niger	No	Paraguay	No	Iceland	No
Rwanda	No	Peru	Yes	Ireland	Yes
Senegal	No	Uruguay	No	Italy	Yes
Sierra Leone	No	Venezuela	Yes	Netherlands	Yes
South Africa	Yes	Bangladesh	Yes	Norway	Yes
Togo	No	China	Yes	Poland	Yes
Tunisia	Yes	Hong Kong	Yes	Portugal	Yes
Uganda	Yes	India	Yes	Spain	Yes
Zaire	No	Indonisia	Yes	Sweeden	Yes
Zambia	No	Iran	Yes	Switzerland	No
Zimbabwe	No	Israel	Yes	Turkey	Yes
Barbados	No	Japan	Yes	United Kingdom	Yes
Canada	Yes	Jordan	Yes	Australia	Yes
Costa Rica	Yes	Korea	Yes	Fiji	No
Dominican Rep.	Yes	Malaysia	Yes	New Zealand	Yes
El Salvador	No	Nepal	No	Papua New Guinea	No