Inequality and Growth in Advanced Economies: An Empirical Investigation*

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Abstract

This paper investigates empirically the effect of income and human capital inequality on economic growth in different regions of the world. In the estimation of a dynamic panel data model that controls for country specific-effects an takes into account the persistency of the inequality indicators, the results show a different effect of inequality on growth depending on the level of development of the region. Specifically, we find a negative effect of income and human capital inequality on economic growth in the whole sample for which there are available data as well as in the low and middle income economies, an effect that vanishes or becomes positive when it comes to higher income countries. Nevertheless, a more exhaustive analysis of the encouraging influence of inequality on growth in the high income economies suggests that it is not stable over time and is highly affected by atypical observations.

JEL classification: O1, O4.

Key words: Human capital and income inequality, economic growth, dynamic panel data model.

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1 Introduction

Does more inequality encourage or discourage economic growth? A large body of empirical evidence has tried to answer this question over the years, however, the literature so far has not provided a conclusive answer to the query. In the early nineties, the results of the theoretical models that formalized a negative effect of wealth inequality on growth and investment rates gained significant relevance since their conclusions were supported by the empirical evidence that used data on income inequality.[1] In particular, the empirical literature found 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. 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 allowed more recent empirical studies to use the temporal dimension of the data to estimate panel data models. However, the estimation of panel data models have challenged the cross-sectional results. For instance, in a panel of countries Barro (2000) finds little association between income inequality and economic growth for a broad number of countries. Moreover, he finds a negative relationship between both variables in poor countries and a positive association in richer places. The most surprising results are those of Forbes (2000). This study controls for country-specific effects and the findings suggest 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.[2] 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 relationship 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 analyze the effect of inequality on growth (e.g. Alesina and Rodrik, 1994; Deiniger and Squire, 1998; Castelló and Doménech, 2002). Recently, Voitchosky (2005) has argued that previous studies have used aggregate measures of inequality, such as the Gini coefficient, which mask the different effect that the lower and upper part of the income

[1] Specifically, part of the literature focused on the political approach in which a median voter chooses the level of redistribution in the economy. Assuming that such redistributive policies are financed by distortionary taxes affecting investment, a more unequal society, in which the median voter favours more redistribution, will experience lower growth rates (Alesina and Rodrik, 1994; Bertola, 1993; Persson and Tabellini 1994). Other studies argued that under the presence of imperfect credit markets poor individuals with no collateral may not undertake a profitable investment project, which implies that the greater the number of restricted individuals, the lower the average investment rate in the society (Galor and Zeira, 1993). See Benabou (1996), Perotti (1996) or Aghion *et. al* (1999) for a comprehensive survey of this literature.

[2] Also estimating a dynamic panel data model but using regional data of the American States, Panizza (2002) finds no 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 econometric specification and the method used to measure inequality.

distribution have on growth. And it is at this stage that the debate in the empirical literature that analyzes the effects of inequality on growth remains.

In this paper we analyze the effect of income and human capital inequality on economic growth in different regions of the world according to their level of development, paying special attention to the Advanced economies or high income OECD countries. This exercise is informative because according to Barro´s (2000) result, the effect of income inequality on economic growth may differ in poor and rich economies. In fact, most of the theoretical channels that predict a negative effect of wealth, income and human capital inequality on growth (e.g. political instability, credit market imperfection, fertility and life expectancy mechanisms) might have a stronger support in developing economies. Therefore, including all countries in the analysis may give misleading conclusions about the real effect of inequality on the per capita income growth rates.

Mainly, we depart from the previous literature in two ways. In the first place, from a methodological point of view, we use the system GMM estimator to control for country specific effects. The reason is that the traditional first difference GMM estimator used by Forbes (2000) may not be appropriate when variables are highly persistent, as it is the case of income and education inequality measures. For example, in a sample that includes all regions in the world more than 90 per cent of the variation in income and human capital inequality measures is cross-sectional, whereas the explanatory power of time dummies in regressions where the dependent variables are the income and human capital Gini coefficients is less than 1 per cent. Thus, by taking first differences most of the variation in the data, which comes from variability across countries, disappears. The benefits of using the system GMM estimator in this context is that, in addition to controlling for unobservable heterogeneity, by estimating an equation in levels, the system GMM estimator keeps the information in the data coming from variability across countries. In fact, in Monte Carlo simulations Blundell and Bond (1998) have shown that under some conditions the system GMM performs better than the first difference when variables are highly persistent. In addition, Hauk and Wacziarg (2006) also show in Monte Carlo simulations that the system GMM estimator has better properties in the estimation of growth equations than the first difference GMM counterpart.

By using the system GMM estimator we find that the influential results of Forbes (2000) are not robust to this econometric technique. In a sample that includes 56 countries for the period 1965-2000 we find a negative coefficient for the income Gini index in the estimation of a conventional growth equation. This result implies that the strong positive effect of income inequality on economic growth, found by Forbes, might not be due to the proper control of country specific effects. Alternatively, the high persistency of the income Gini coefficient and the fact that it is measured with error (see Atkinson and Brandolini, 2001) may rise some doubts whether the first difference GMM is an appropriate estimator in this context.

In the second place, in addition to analyzing the relationship between income inequality and economic growth, we also use human capital inequality measures. In fact, the role played by human capital inequality on economic growth is present in most of the models that analyze the effect of inequality on growth under imperfect credit markets (e.g. Galor and Zeira, 1993; Mookherjee and Ray, 2003). Moreover, the latest advances in the theoretical literature also point out to human capital inequality and its influence on demographic variables as alternative channels that predict a negative relationship between inequality and growth. In particular, Castelló-Climent and Doménech (2007) examine how human capital inequality may discourage growth by reducing life expectancy and investment in education, rather than by increasing fertility, as in De la Croix and Doepke (2003) and Moav (2005). Nevertheless, it is worthy to point out that these mechanisms should have more support in developing countries where differences in fertility and life expectancy among individuals are more pronounced. On the contrary, in rich economies, the role of human capital inequality on growth could be different and might respond to the demand of highly educated individuals in a rapid process of technological change.

Interestingly, the results found in this paper are in accordance with these predictions. Specifically, we find that more human capital inequality discouraged the per capita income growth rates in most parts of the world during the period 1965-2000. Mainly, in less developing countries where the life expectancy and fertility channels seem that played an outstanding effect. On the contrary, this negative effect vanishes when it comes to higher income economies. Nevertheless, although we find that greater human capital inequality encouraged the per capita income growth rates of the European economies during the period 1980-2000, a robustness check suggests that this result is highly influenced by atypical observations.

Likewise, we also find a different effect of income inequality on the per capita income growth rates depending on the level of development. Using an updated version of the Deiniger and Squire´s (1996) data set, we find that the negative influence of a more unequal distribution of income on growth in developing countries becomes positive in the Advanced and European economies. Moreover, the use of a higher quality data set from the Luxemburg Income Study for the higher income economies displays similar results.

The organization of the paper is as follows. In the next Section we discuss the data and the model. In Section 3 we display the results about the influence of income and human capital inequality on economic growth in several samples that include the total available data, Developing, Advanced and European Economies. In Section 4 we focus on the Advanced economies and use alternative inequality indicators to examine whether the different parts of the distribution have different effects on economic growth. Moreover, we split the whole sample into different sub periods to see if the different effect of inequality on growth found in the European economies is stable over time and if it has been influenced by the European Monetary Union. Section 5 contains the conclusions reached.

2 Econometric Model and Data

2.1 Econometric Model

Most of the empirical studies that have analyzed 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. One of the main criticisms of these kind of regressions is that they suffer from two inconsistency sources. On the one hand, 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. On the other hand, they do not address properly the treatment of some explanatory variables that, according to the theory, should be considered to be endogenous. Both remarks seem extremely important in the relationship between inequality and growth as suggested by Forbes´s (2000) results. Therefore, we propose to analyze the effect of income and human capital inequality on economic growth by estimating the following standard growth equation:

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

Reorganizing we can rewrite equation (1) as a dynamic model:

$$\ln y_{i,t} = \widetilde{\beta} \ln y_{i,t-\tau} + \widetilde{\gamma} Inequality_{i,t-\tau} + X_{i,t-\tau}\widetilde{\delta} + \widetilde{\xi}_t + \widetilde{\alpha}_i + \widetilde{\varepsilon}_{i,t} \tag{2}$$

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 $\widetilde{\varepsilon}_{i,t} = \tau\varepsilon_{i,t}$. The definition of variables is as follows, $y_{i,t}$ is the real GDP per capita in country i measured at year t, τ is a five-year span, $Inequality_{i,t-\tau}$ measures income and human capital inequality in country i at the beginning of the period, β, γ and δ represent the parameters of interest that are estimated, 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 over time.

In order to reduce any omitted variable bias, matrix $X_{i,t-\tau}$ includes k explanatory variables, suggested in the literature as important determinants of the growth rates (e.g. Barro, 2000). The empirical studies analyzing growth usually estimate a broader 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 to be estimated will control for initial conditions and for 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 (lny) and the initial stock of human capital, proxied by the average years of male secondary and tertiary education of the population aged 25 years and over (*Educ*).[3] The determinants of the steady state include some variables that answer for government policies and others that refer to optimal decisions by private agents. These variables include the government share of real GDP (*G/GDP*); total trade, measured as exports plus imports divided by real GDP (*Trade*) and the inflation rate, measured as the annual growth rate of consumer prices (*Inflation*). Human and physical capital accumulation are ruled out from the set of controls because they are endogenous in the model; most of the mechanisms that predict a negative effect of inequality on growth work through a discouraging effect on the investment rates.

The most common approach to estimate a dynamic panel data model has been the first difference Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond (1991). The idea of this estimator is to take first differences to eliminate the source of inconsistency, that is α_i, and use the levels of the explanatory variables lagged two and further periods as instruments. In order for the first difference GMM estimator to be consistent we need to assume that the errors are not second order serially correlated and that the explanatory variables are weakly exogenous.

However, although the first difference GMM estimator deals properly with the problem of unobservable heterogeneity, it has some shortcomings in the estimation of equation (2). The first has to be with the characteristic of persistency of the variables included in this equation. These variables, particularly income and human capital inequality measures, vary significantly across countries but remain quite stable within a country. For instance, Table 1 shows that more than 90 per cent of the variation in income and human capital inequality measures is cross-sectional, whereas the explanatory power of time dummies in regressions where the dependent variables are the income and human capital Gini coefficients is less than 1 per cent. Thus, by taking first differences most of the variation in the data, which comes from variability across countries, disappears. This fact may indeed increase the measurement error bias by increasing the variance of the measurement error relative to the variance of the true signal (Griliches and Hausman, 1986). Moreover, Blundell and Bond (1998) point out that when explanatory variables are persistent, the lagged levels of the explanatory variables are weak instruments for the variables in differences. They show that in small samples the shortcoming of weak instruments translate into a large finite sample bias.

Therefore, an econometric technique that exploits the bulk of the variation in the data would be preferable in order to improve the precision of the estimated coefficients. By adding the original equation in levels to a system of equations that also include equations in first differences, the system GMM estimator is particularly useful in our context since, in addition to controlling for country-specific effects, it preserves the cross-country dimension of the data that is lost when only the first differenced equation is estimated (e.g. Arellano and Bover, 1995; Blundell and Bond, 1998) .

In the system GMM estimator the equations in first differences eliminate the fixed effect in

[3] Evidence suggests that higher male levels of education accounts more for growth than primary and female education (see for example Barro, 2000).

the model. Moreover, the difference equations are combined with equations in levels, which are instrumented with the lagged first differences of the corresponding explanatory variables. In order to use these additional instruments, we need the identifying assumption that the first differences of the explanatory variables are not correlated with the specific effect, that is, although the specific effect may be correlated to the explanatory variables, the correlation is supposed to be constant over time. If the moment conditions are valid, Blundell and Bond (1998) show that in Monte Carlo simulations the system GMM estimator performs better than the first difference GMM estimator. We can test the validity of the moment conditions by using the conventional test of overidentifying restrictions proposed by Sargan (1958) and Hansen (1982) and by testing the null hypothesis that the error term is not second order serially correlated. Furthermore, we will test the validity of the additional moment conditions associated with the level equation with the difference Hansen test.

2.2 Data

The sources of the data used are as follows. The data on real GDP per capita (*lny*), government spending (*G/GDP*), measured as government share of real GDP, and total trade (*Trade*), measured as exports plus imports to real GDP, are taken from PWT 6.2 by Heston, Summers and Aten. The latest version of the PWT has updated the measures of per capita income up to 2005, which allows as to use one more period in the sample, 1960-2005. Inflation rate (*Inflation*), measured as the annual growth rate of consumer prices, is taken from the Global Development Growth Data Base compiled by Easterly and Sewadeh (2002).

The income Gini coefficient ($Gini^y$) 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 A. Even though we can include only twelve more countries, Table A shows that most of them are developing countries and six of them are in Africa. This enlargement is one step further in achieving a data set that represents all areas in the world, some of them with no observations in Forbes' sample. On balance, there is a total of 56 countries with at least two observations of the income Gini index.

In the second part of the paper we focus on the effect of inequality on growth in a sample of economically Advanced economies and European countries. Thus, we use the Luxemburg Income Study that provides improved data for income inequality measures with regard to quality and comparability across countries. The main drawback of the LIS data set is that it only contains data for a reduced sample of wealthy economies starting in 1980.

A more comprehensive data set on inequality measures is that for human capital inequality variables ($Gini^h$, $Quintile^h$), which are available for 108 countries during the period 1960-2000. The source of human capital inequality measures is Castello and Domenech (2002) and the education variable (*Educ*) is taken from the latest Barro and Lee' (2001) data set.[4]

3 Empirical Results

The role played by human capital accumulation is present in most of the models that analyze the relationship between inequality and growth. Furthermore, inequality in education is highly related to inequality in opportunities, which can be very acute in the presence of credit market constraints. For instance, under imperfect credit markets and indivisibilities in the accumulation of human capital, Galor and Zeira (1993) find that the greater the share of the population credit constrained, the lower the average human capital in the economy. In this model wealth transmission from parents to children depends on the parents´ human capital. As a result, the initial distribution of wealth is mainly driven by the initial distribution of human capital.

Mechanisms that point out different fertility patterns among individuals with different levels of education also predict that the distribution of education on one side and decisions on human capital investment and fertility on the other are highly related (e.g. De la Croix and Doepke, 2003; Moav, 2005). In these models parents with lower human capital choose to have a higher number of children and less education for them, which hampers the number of skilled individuals in the future and therefore the average level of human capital and growth rates in the economy. Recently, other papers have also pointed out that the initial distribution of education may hamper the human capital investment rates by reducing the average life expectancy. Castello-Climent and Doménech (2007) show that when parents education influences offspring life expectancy, as it is shown by empirical evidence (e.g. Case et al., 2002; Currie and Moretti, 2003), the initial distribution of education, by affecting life expectancy, has outstanding effects on a country´s average rate of investment in human capital.

Therefore, in the fist place we check whether the distribution of education has had any effect on the per capita income growth rates in different regions of the world. In fact, we should expect that the negative effect of human capital inequality on growth, predicted from the theoretical models, should be more acute in developing countries, where the difference between life expectancy and fertility patterns among the strata of the population are more acute. On the contrary, the role that the demographic channels are expected to play in richer economies is likely to be less important.

Using available data for the distribution of education, computed by Castello and Domenech (2002), we examine the effect of human capital inequality on economic growth during the period

[4] Table A reports data on 12 countries that were not included in Forbes' sample. These countries are Algeria, Iran, Israel, Jordan, Ghana, Mauritaia, Mauritius, South Africa, Uganda, Honduras, Jamaica and Taiwan. However, unlike Forbes´ study, Table A does not report data on Bulgaria because this country is not included in Castello and Domenech's (2002) data set.

1965-2005. The results, displayed in Table 2, show a clear negative and statistically significant effect of the human capital Gini coefficient on the per capita income growth rates in a sample of 102 countries that include all countries in the world for which there are available data. Moreover, this effect is not only statistically significant at the 1 per cent level but it is also considerable in quantitative terms; an increase in 0.1 points in the human capital Gini index reduces the annual growth rate by 0.51 per cent. The results of the other variables are also as expected; a negative coefficient of the initial per capita income, showing conditional convergence, a positive effect of the educational variable and a negative one of the government expenditure. Moreover, we find that more openness, measured through the share of total trade, has had a positive influence on a country´s per capita income growth rate whereas more inflation has had a negative one.

Once we have examined the effect of human capital inequality on the growth rates in the whole sample, we focus on different regions of the world to test whether the influence of human capital inequality on growth differs in countries with different levels of development. The results show that the estimated coefficient in the whole sample practically holds when we reduce the countries to include only developing economies, as displayed in column (2).[5] Likewise, when we restrict the sample to OECD countries the estimated coefficient of the human capital Gini index continues having a negative and statistically significant impact at the 1 per cent level on the per capita income growth rate, though the economic impact is smaller in absolute value. Nevertheless, once we remove the countries that are not classified as high income economies from the OECD sample the negative effect on the growth rates of an increase in human capital inequality is no so evident. The results displayed in column (4) for the Advanced or high income OECD economies show that the estimated coefficient of the human capital Gini index reduces more than half and stops being statistically significant at the standard levels.[6] Moreover, the absence of a negative effect from human capital inequality on growth is even more clear in the European economies. Column (5) displays a positive coefficient of the human capital Gini index, though it is not statistically significant, for a sample of 20 European economies.

According to some theoretical models, human capital inequality could affect economic growth rates through its influence on demographic variables. Thus, in the remaining columns we include the fertility rates and a measure of the life expectancy in the set of controls. In line with the theoretical predictions, columns (6-8) show that once we control for demographic variables the negative and statistically significant coefficient of the human capital Gini index disappears in the World sample as well as in the Developing and OECD economies. In fact, we find that longer life expectancy has had a strong positive influence on the growth rates whereas more fertility rates have had a discouraging

[5] Developing countries include low and middle income countries ($11,115 or less) as classified by the World Bank in 2007. Income groups are classified according to 2006 gross national income per capita.

[6] The Advanced economies include the high income OECD economies as classified by the World Bank. OECD cuntries not classified as high income economies in our sample inlcude Hungary, Mexico, Poland and Turkey.

effect on growth. Moreover, as expected, the non existent influence of human capital distribution on growth in the Advanced and European economies is not affected by controlling for the demographic measures.

Up to now we have examined the effect of human capital inequality on economic growth. However, it may be possible that the human capital inequality measure is picking up an income inequality effect. Therefore, in Table 3 we examine the individual and joint effect of income and human capital inequality on the per capita income growth rates in different regions of the world. Nevertheless, whereas there are data for human capital inequality measures for 108 countries over the period 1960-2000, the availability of data of income inequality measures for a broad number of countries and periods is scarce. Specifically, by controlling for income inequality measures the number of countries halves and in many of these countries there are only data for two periods.

Table 3 displays the results of the effect of human capital and income inequality on economic growth in the reduced sample of 56 countries for which there are available data on income inequality measures. With regard to human capital inequality, the results display a negative coefficient of the human capital Gini index in all samples, though in the Advanced and European economies this coefficient is not statistically significant at the standard levels. Also in line with the previous findings, the lower part of the table shows that the negative coefficient of the human capital Gini index in the World, Developing and OECD samples stops being statistically significant once we control for the life expectancy and the fertility rates, suggesting that some of this negative effect is driven through the demographic variables.

The independent effect of income inequality on growth is displayed in the second column of every group of countries. With regard to the whole sample, column (2) shows that an increment in income inequality has hampered the growth rates in the whole sample that includes all countries for which there are available data. This result is very important because it highlights that the striking findings of Forbes (2000), who finds a strong positive and statistically significant coefficient for the income Gini index by using the first difference GMM estimator, could be driven by the fact that inequality measures are highly persistent and measure with error and not by the omission of country specific effects in the model.

The results also suggest that the influence of income inequality on economic growth in the Advanced and European countries is different from that found in the rest of the world. Specifically, we find a negative coefficient in the sample of Developing and OECD countries, though the coefficient is only statistically significant in the latter. Interestingly, in line with the demographic channels, we also find that the negative effect of income inequality on growth, if any, disappears once the measures of life expectancy and fertility rates are accounted for (see lower part of the Table). On the contrary, the estimated coefficient of the Gini index is positive, though not statistically significant at the standard levels, for the Advanced and European economies.

Finally, we control for both human capital and income inequality to test whether they have any independent effect on growth (results are displayed in the third column of every group of countries). The results can be summarized as follows. Firstly, the coefficient of the human capital and income Gini indexes are negative and statistically significant in the sample that includes all countries, which suggests that income and education inequality have had a negative and independent effect on the per capita income growth rates. Moreover, the fact that these coefficients stop being statistically significant once fertility and life expectancy are included in the set of controls gives support to the predictions of the demographic mechanisms. Secondly, whereas the negative effect of a more unequal distribution of education holds, the coefficient of the income Gini index is close to zero in the sample of Developing countries. Moreover, once the demographic variables are included, the estimated coefficient of income Gini index is even positive and statistically significant at the 5 per cent level. Finally, in the Advanced and European economies we also find a different effect of income and human capital inequality on growth. Specifically, the estimated coefficient of the human capital Gini index continues being negative, though not statistically significant. However, the evidence suggest that a greater inequality in the distribution of income has had a beneficial effect on the per capita income growth rates of the Advanced and European economies; the coefficient of the income Gini index is positive and statistically significant at the 10 and 5 per cent significance level respectively.

To sum up, when we control for both, income and human capital inequality, whereas we find a negative coefficient of the human capital Gini index in all samples the effect of income inequality on growth differs across regions. Specifically, more income inequality seems to be related to higher growth rates in rich economies. The differential effect of human capital and income inequality in the Advanced and European economies is analysed in more detail in the remaining part of the paper.

4 Income and Human Capital Inequality in the Advanced Economies

In this section we examine in more detail the evolution of income and human capital inequality over time and its effect on the per capita income growth rates in the high income OECD economies and in the European countries.

In Figure 1 we plot the income Gini coefficient for the Advanced economies. For the few countries for which there are available data in the seventies, we observe a reduction in the income Gini coefficient over this 10 year span. The reduction in income inequality is found not only in higher inequality countries such as the United States and Canada but also in lower income inequality economies such as Germany or Sweden. However, the behaviour of the income Gini coefficient changes dramatically in the eighties. In particular, from 1980 to 1990 we observe an increase in the income Gini coefficient in most of the Advanced economies. The greater increase is found in the United States, United

Kingdom, Australia and Sweden. Moreover, Figure 1 also shows that the tendency of increasing income inequality continues in the nineties as well. Some exceptions are Denmark, the Netherlands, France, Ireland and Greece, which slightly reduced income inequality over this period. However, in spite of the general increment in income inequality in the Advanced economies since 1980, in year 2000 there are noticeable differences among these countries. Specifically, income Gini coefficients above 0.33 can be found in the United States, United Kingdom, Spain and Greece. On the other extreme are Denmark, the Netherlands, Finland, Norway or Sweden, with income Gini coefficients below 0.26.

The pattern of human capital inequality over this period differs from that observed with income inequality. Broadly, human capital inequality has remained constant over the whole period. In fact, Figure 2 shows that from 1990 to 2000 most of the countries have maintained their relative positions, being located very close to the diagonal line. Nevertheless, the variation in human capital inequality across countries is higher than that observed with income inequality. For instance, in year 2000 Portugal and Italy displayed a human capital Gini coefficient close to 0.4 and 0.35, respectively. On the other extreme are Norway, the United States, Canada and New Zealand with a Gini coefficient close to 0.1. As a result, human capital inequality displays a lower average and greater variation than income inequality. In particular, the statistics for the Advanced economies in year 2000 show an average human capital Gini coefficient of 0.20 with a standard deviation equal to 0.07, whereas the average income Gini coefficient is 0.29 with a standard deviation of 0.04.

Next, we examine the effect of human capital and income inequality on the per capita income growth rates in different samples that include higher income countries. In the first place, we will split the whole sample into different subperiods. This will allow us to check if the effect of inequality on growth has been stable over time and if the European Monetary Union has had any influence on the differential effect found in the European countries. In particular, we will compare the effect of inequality on growth in the Euro area with that observed in countries with similar levels of development such as the whole European region and other Advanced or high per capita income economies.[7]

Moreover, we will complement the information provided by the Gini coefficient with additional measures of the different parts of the distribution such as the distribution of education by quintiles or ratios of several income percentiles. The use of these additional measures is helpful because the Gini coefficient is an aggregate measure of inequality and it does not provide any information on whether the lower an upper part of the distribution have different effects on the growth rates. In fact, Voitchosky (2005) states that the use of a unique and aggregate measure of inequality, such as the Gini coefficient, may mask the complex effect that the different parts of the income distribution may have on economic growth. Specifically, using the Luxemburg Income Study data set she finds

[7] The countries that belong to the Euro Area in our sample are: Austria, Belgium, France, Finland, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain.

that inequality at the top end of the income distribution is positively related to economic growth, whereas inequality at the bottom end of the distribution has a negative impact on subsequent growth rates.

Table 4 displays the results for human capital inequality, measured through the Gini coefficient and the distribution of education by quintiles. In these regressions we also control for the standard determinants of growth and for time dummies, in line with the previous tables. However, to save space we only show the estimated coefficients for the inequality variables. The first column shows the results for the human capital Gini coefficient and for the distribution of education by quintiles for the Advanced, European and Euro economies for the whole period, 1965-2005. In the remaining columns we have split the whole period into subperiods of equal length to test whether the effect of human capital inequality differs over time.

The results regarding the Advanced economies show an effect of human capital inequality on economic growth that is not stable over time, in some periods the estimated coefficient of the Gini index is negative whereas at the end of the eighties and nineties it is positive, though in any case it is statistically significant at the standard levels. In fact, the estimated coefficient of the human capital Gini index is only statistically significant in the recent years. In particular, during the period 1995-2005 the results suggest that more human capital inequality discouraged the growth rates of the Advanced economies; the estimated coefficient of the Gini index is -0.157 and it is statistically significant at the 5 per cent level. Likewise at different parts of the distribution, the results with the quintiles show that a greater share of the education attained by the majority of the society had a beneficial effect on the per capita income growth rates, whereas a greater share of education concentrated on the top 20 per cent of the highest educated individuals discouraged growth.

Nevertheless, the results for the European economies are somehow different. Although the estimated coefficient of the human capital Gini index is also negative during the period 1995-2005, it is not statistically significant at the standard levels. Moreover, the Gini coefficient and the quintiles suggest that human capital inequality had a positive instead of a negative effect on the economic growth rates during the period 1980-1995.

A positive effect of a more unequal distribution of education on the growth rates is also found in the Euro Area, mainly from 1980 to 2000. In fact, even for the whole period the estimated coefficient of the 5^{th} Quintile in the distribution of education is positive and statistically significant at the 10 per cent level, which leads to the suggestion that the European Monetary Union is not the cause of such an effect. However, given the high disparities in the inequality measures (e.g. the average human capital Gini index in Portugal (0.474) is almost 3 times higher than that in the Netherlands (0.170)) it is possible that an extreme value is influencing these results. Thus, to check the robustness of the positive effect of human capital inequality on the growth rates we have repeated the previous exercise removing one country at a time. Interestingly, Table 5 shows that the results are quite sensitive to the inclusion of Portugal in the sample. In particular, the positive and statistically significant coefficient of the human capital Gini coefficient and the top quintile for the period 1985-2000 disappears once Portugal is excluded from the sample. For example, once we rule out Portugal the estimated coefficient for the fifth quintile for the period 1990-2000 found in Table 4 (0.163 (st. dv. 0.064) reverse sign and stops being statistically significant (-0.154 (st. dv. 0.154)), which leads to the suggestion that the positive influence of human capital inequality on economic growth is not robust and is highly influenced by one of the countries with extreme values in the inequality indicator.

As for the effect of income inequality on economic growth, we have analysed the stability over time with different measures from the Luxembourg Income Study data set. Nevertheless, in spite of its improvement in the quality of the data, one of the main drawbacks of the LIS data set is the lack of observations for a broad number of countries during a long time period. For example, there are no data for Portugal or New Zealand and for most countries the first observation starts in 1980. As a result, we are forced to divide the whole period into two subperiods: 1975-1990 and 1990-2005.

The results, displayed in Table 6, show a positive and statistically significant coefficient of the income Gini index in the sample of Advanced economies during the whole period 1975-2005.[8] However, the fact that the estimated coefficient of the income Gini index is negative in the period 1975-1990 suggests that this effect is mainly driven by the positive effect on growth of an increase in income inequality in the latest period of the sample, 1990-2005. Among the percentile ratios, this result is also reflected in a positive an statistically significant coefficient of the ratio between the income reached by the 20 per cent of individuals with the highest income by the 20 per cent of individuals with the lowest income, that is, this ratio accounts for how may times the richest 20 per cent have more income than the poorest 20 per cent.

A similar result is found in the European countries and in the Euro Area during the period 1990-2005.[9] In particular, the estimated coefficient of the Gini index is 0.079 for the Advanced economies, 0.076 for the European countries and 0.071 for the Euro Area. Likewise, the estimated coefficient of the percentile ratio between the richest 20 per cent and the poorest 20 per cent is 0.010 in the sample of the Advanced economies, 0.012 in the European region and 0.015 in the Euro Area.

The fact that the positive effect of income inequality on growth from 1990 onwards is also found in the broader sample of the Advanced economies, which includes countries such as the United States with high income inequality and high per capita income growth rates, minimizes the possibility that the European Monetary Union has influenced the results. Moreover, we have also tested the robustness of the results to different time periods. We find similar results for the period 1985-2005 and for the period 1980-2005, which suggests that the positive effect was previous to

[8] Note that this result differs of that found in Table 3 for the period 1965-2000 for 20 Advanced economies using the World Bank data set.

[9] Due to a lack of sufficient observations we can not report any result for the period 1975-1990 for the Euro Area.

the establishment of the EMU. Nevertheless, in line with the analysis of human capital inequality we have also analysed whether any country belonging to the Euro Area may be the responsible of this positive effect. Results displayed in Table 7 show that when we remove one country at a time the estimated coefficient of the Gini index is always positive and quite stable in the sample of the Advanced economies, though it is sensitive to the countries included in the reduced sample of European and Euro Area countries.

Overall, in view of these results we can not conclude that a more uneven distribution of human capital or income may rise the growth rates of the European economies since the effect has not been stable over time. Moreover, we have found that the positive influence of human capital inequality on the growth rates is driven by atypical observations. Furthermore, the scarcity of available data for income inequality measures make it difficult to carry out a proper empirical test.

5 Conclusions

In this paper we have analysed the effect of income and human capital inequality in different regions of the world that include developing as well as rich economies. The estimation of a dynamic panel data model that controls for country specific characteristics suggests that income and human capital inequality have a different effect on growth in regions with different levels of development.

Using data for human capital Gini coefficients and the distribution of education by quintiles we find that more human capital inequality has discouraged the growth rates in most of the regions in the world. In accordance to some theoretical models, the negative effect is found in less developed countries where the relationship between human capital inequality and demographic variables is stronger. On the contrary, we do not find a clear effect in the sample of higher income economies. In particular, whereas we obtain a positive effect of a more unequal distribution of human capital on the growth rates of the European economies during the period 1980-2000, a simple test of atypical observations shows that this result is not robust.

With regard to the effect of income inequality on growth, we find different effects according to the level of development; a negative effect in the less developed countries and a positive one in the higher income economies. Moreover, the positive effect in the richer countries is found not only with the World Bank income inequality measures but also with the higher quality LIS data set, which shows that a greater share of income accruing to the richest twenty per cent of individuals regarding to the poorest 20 per cent has had a positive and statistically significant influence on the growth rates of the Advanced and European economies in recent years.

Overall, the results suggest that income and education inequality have had a different effect on the growth rates of several economies depending on their level of development. In particular, the results seem to be negative for low and middle income countries and in some cases positive for higher income economies. Nevertheless, the positive effect of inequality on economic growth found in the

Advanced and European economies is not robust to atypical observations and is not stable over time, which suggest that a trade-off between equity and efficiency might not be a concern in these economies.

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Figure 1- Income Gini coefficient 1970-2000

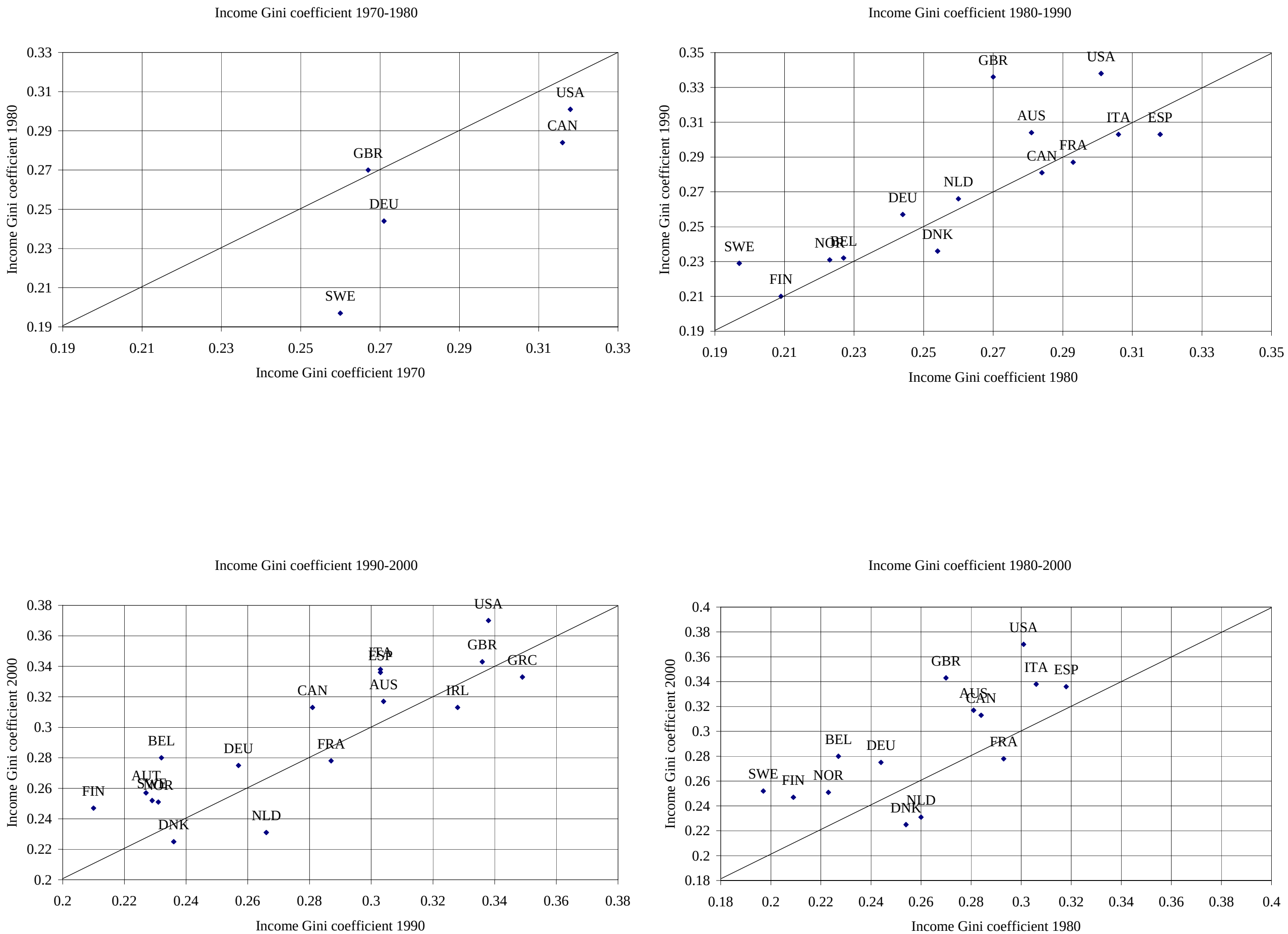

Figure 2- Human Capital Gini coefficient 1960-2000

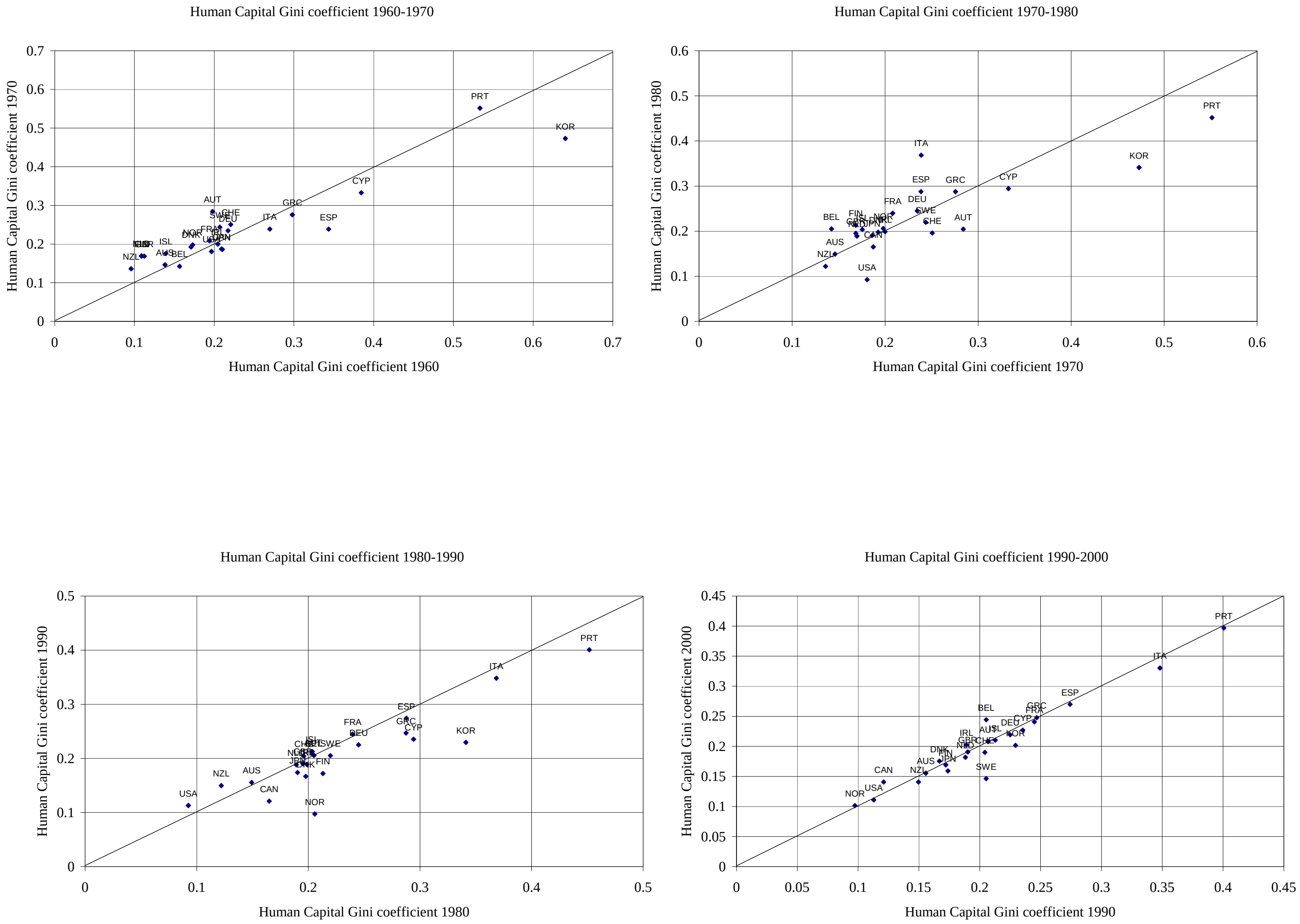

Table 1

Income and Human Capital Inequality

	R^2 from regressions on country and time dummies				
Dependent variable	Country dummies	Time dummies	Country and time dummies	Obs.	Countries
$Gini^y$	0.920	0.019	0.924	256	56
$Gini^h$	0.901	0.042	0.952	919	105

Note: Pooled OLS estimation.

Table 2
Human Capital Inequality and Economic Growth
Whole Sample. System GMM

	World (1)	*Developing* (2)	*OECD* (3)	*Advanced* (4)	*Europe* (5)	*World* (6)	*Developing* (7)	*OECD* (8)	*Advanced* (9)	*Europe* (10)
$Gini^h_{t-\tau}$	-0.050^a	-0.048^a	-0.034^a	-0.015	0.012	0.008	0.010	-0.000	-0.024	0.016
	(0.015)	(0.017)	(0.011)	(0.014)	(0.015)	(0.013)	(0.015)	(0.011)	(0.015)	(0.015)
$lny_{t-\tau}$	-0.006^a	-0.005^a	-0.025^a	-0.034^a	-0.026^a	-0.018^a	-0.011^a	-0.039^a	-0.038^a	-0.033^a
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$Educ_{t-\tau}$	0.002	-0.000	0.002^c	0.001	0.002	-0.003	-0.006	0.003^a	0.002	0.002^c
	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
$(G/GDP)_{t-\tau}$	-0.037	-0.033	-0.052^b	-0.063^a	-0.046^c	-0.031	-0.040	-0.053^b	-0.060^a	-0.035
	(0.026)	(0.028)	(0.025)	(0.022)	(0.027)	(0.025)	(0.028)	(0.022)	(0.022)	(0.027)
$Trade_{t-\tau}$	0.010^a	0.013^a	0.011^a	0.008^b	0.015^a	0.005^c	0.009^b	0.012^a	0.008^b	0.015^a
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)
$Inflation_{t-\tau}$	-0.002^a	-0.002^a	-0.035^a	-0.026	-0.026^a	-0.002^a	-0.002^a	-0.030^a	-0.012	-0.024^a
	(0.000)	(0.000)	(0.007)	(0.019)	(0.008)	(0.000)	(0.000)	(0.006)	(0.020)	(0.009)
$lnFERT_{t-\tau}$						-0.040^a	-0.043^a	-0.012^a	-0.012^b	-0.002
						(0.007)	(0.009)	(0.004)	(0.006)	(0.007)
$lnLE_{t-\tau}$						0.047^a	0.034^c	0.129^a	0.014	0.121^b
						(0.018)	(0.020)	(0.036)	(0.050)	(0.059)
Constant	0.105^a	0.086^c	0.279^a	0.359^a	0.277^a	0.049	0.052	-0.145	0.347^c	-0.174
	(0.038)	(0.047)	(0.030)	(0.032)	(0.038)	(0.074)	(0.887)	(0.133)	(0.186)	(0.223)
Countries	102	70	27	23	20	101	70	27	23	20
Obs	744	474	236	204	172	732	470	236	204	172
AR (2) test	[0.129]	[0.117]	[0.558]	[0.094]	[0.728]	[0.171]	[0.139]	[0.605]	[0.011]	[0.690]
Hansen J test	[0.001]	[0.001]	[0.209]	[0.444]	[0.839]	[0.001]	[0.005]	[0.782]	[0.981]	[0.995]
Diff Hansen	[0.029]	[0.597]	[1.000]	[0.999]	[1.000]	[0.270]	[0.457]	[1.000]	[0.999]	[1.000]

Note: Robust standard errors in parenthesis. a, b and c are 1, 5 and 10 per cent significance level respectively. The set of controls also include period dummies. The period of analysis is 1965-2000. The instruments are the levels of the explanatory variables lagged two periods and further lags until a maximum of 4. In addition to these variables, the system-GMM also uses as instruments for the level equation the explanatory variables in first differences lagged one period. Developing countries include low and middle income countries as classified by World Bank in 2007 and Advanced countries include OECD countries except Hungary, Mexico, Poland and Turkey.

Table 3

Human Capital Inequality, Income Inequality and Economic Growth

Reduced Sample. System GMM

	World			Developing			OECD			Advanced			Europe		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$Gini^h_{t-\tau}$	-0.028^c		-0.025^c	-0.036^b		-0.036^b	-0.031^b		-0.022	-0.011		-0.011	-0.004		-0.021
	(0.015)		(0.015)	(0.014)		(0.015)	(0.014)		(0.016)	(0.021)		(0.021)	(0.019)		(0.021)
$Gini^y_{t-\tau}$		-0.053^c	-0.061^b		-0.017	0.000		-0.042^b	-0.028		0.038	0.038		0.040	0.054^c
		(0.027)	(0.025)		(0.026)	(0.024)		(0.021)	(0.023)		(0.028)	(0.028)		(0.026)	(0.030)
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ and time dummies															
Countries	56	56	56	31	31	31	24	24	24	20	20	20	16	16	16
Obs	244	244	244	119	119	119	125	125	125	104	104	104	79	79	79
AR (2) test	[0.076]	[0.079]	[0.064]	[0.046]	[0.042]	[0.098]	[0.912]	[0.992]	[0.968]	[0.954]	[0.979]	[0.954]	[0.960]	[0.964]	[0.934]
Hansen J test	[0.045]	[0.121]	[0.115]	[0.773]	[0.709]	[0.852]	[0.857]	[0.857]	[0.961]	[0.969]	[0.969]	[0.989]	[0.987]	[0.987]	[0.997]
Diff Hansen	[0.879]	[0.977]	[0.967]	[0.986]	[0.948]	[0.998]	[1.000]	[1.000]	[1.000]	[0.999]	[0.999]	[0.999]	[1.000]	[1.000]	[1.000]

Controlling for fertility rates and life expectancy

	World			Developing			OECD			Advanced			Europe		
$Gini^h_{t-\tau}$	-0.002		-0.004	0.009		0.011	-0.009		-0.015	-0.020		-0.027	-0.006		-0.030
	(0.014)		(0.013)	(0.017)		(0.028)	(0.016)		(0.018)	(0.024)		(0.024)	(0.020)		(0.023)
$Gini^y_{t-\tau}$		0.021	0.024		0.066^b	0.068^b		0.011	0.022		0.046	0.051^c		0.043	0.066^b
		(0.022)	(0.021)		(0.028)	(0.028)		(0.025)	(0.028)		(0.030)	(0.030)		(0.028)	(0.033)
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$,$lnFERT_{t-\tau}$, $lnLE_{t-\tau}$ and time dummies															
Countries	55	55	55	31	31	31	24	24	24	20	20	20	16	16	16
Obs	237	237	237	119	119	119	125	125	125	104	104	104	79	79	79
AR (2) test	[0.048]	[0.053]	[0.054]	[0.025]	[0.039]	[0.019]	[0.856]	[0.833]	[0.779]	[0.923]	[0.983]	[0.990]	[0.947]	[0.945]	[0.889]
Hansen J test	[0.300]	[0.333]	[0.444]	[0.933]	[0.933]	[0.975]	[0.988]	[0.988]	[0.996]	[0.977]	[0.997]	[0.999]	[0.999]	[0.999]	[1.000]
Diff Hansen	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[0.999]	[1.000]	[1.000]	[1.000]

Note: Robust standard errors in parenthesis. a, b and c are 1, 5 and 10 per cent significance level respectively. The period of analysis is 1970-2000. The instruments are the levels of the explanatory variables lagged two periods and further lags until a maximum of 4. In addition to these variables, the system-GMM also uses as instruments for the level equation the explanatory variables in first differences lagged one period .

Table 4
Human Capital Inequality and Economic Growth
Dependent variable: per capita income growth rate. System GMM

	1965-2005	1965-1975	1970-1980	1975-1985	1980-1990	1985-1995	1990-2000	1995-2005
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Advanced Countries				
Gini^h	-0.015	-0.024	0.001	-0.041	-0.001	0.013	0.004	**-0.157**^{b}
	(0.014)	(0.050)	(0.053)	(0.037)	(0.053)	(0.040)	(0.054)	(0.067)
1^{st} Quintile^h	0.041	-0.044	0.035	0.201	0.034	0.052	0.004	0.145
	(0.028)	(0.116)	(0.094)	(0.143)	(0.086)	(0.081)	(0.079)	(0.090)
3^{rd} Quintile^h	0.015	0.024	-0.041	0.012	-0.037	-0.085	0.054	**0.199**^{b}
	(0.018)	(0.067)	(0.061)	(0.041)	(0.058)	(0.080)	(0.085)	(0.084)
5^{th} Quintile^h	-0.016	-0.116	-0.028	-0.024	0.027	0.073	0.071	**-0.270**^{b}
	(0.024)	(0.107)	(0.078)	(0.059)	(0.063)	(0.070)	(0.070)	(0.121)
Obs.	204	66	68	69	69	69	69	69
Countries	23	23	23	23	23	23	23	23
				European countries				
Gini^h	0.012	-0.012	-0.030	-0.001	**0.081**^{b}	0.050	0.048	-0.046
	(0.015)	(0.044)	(0.037)	(0.048)	(0.031)	(0.035)	(0.037)	(0.042)
1^{st} Quintile^h	-0.009	0.156	0.091	0.039	**-0.149**^{b}	-0.063	-0.067	0.077
	(0.031)	(0.106)	(0.077)	(0.076)	(0.064)	(0.072)	(0.082)	(0.082)
3^{rd} Quintile^h	-0.017	-0.006	0.019	0.002	**-0.122**^{b}	-0.044	-0.015	0.102
	(0.021)	(0.054)	(0.058)	(0.000)	(0.046)	(0.074)	(0.059)	(0.069)
5^{th} Quintile^h	0.026	-0.081	-0.032	0.012	**0.138**^{a}	**0.104**^{c}	0.087	-0.012
	(0.026)	(0.091)	(0.077)	(0.064)	(0.048)	(0.056)	(0.053)	(0.051)
Obs.	172	52	56	60	60	60	60	60
Countries	20	20	20	20	20	20	20	20
				Euro Area				
Gini^h	0.019	0.013	0.025	0.017	**0.058**^{b}	**0.106**^{a}	**0.091**^{c}	0.029
	(0.016)	(0.023)	(0.021)	(0.077)	(0.024)	(0.032)	(0.045)	(0.049)
1^{st} Quintile^h	-0.042	-0.088	-0.057	-0.034	**-0.085**^{c}	**-0.135**^{b}	-0.124	-0.043
	(0.030)	(0.054)	(0.054)	(0.051)	(0.045)	(0.055)	(0.075)	(0.081)
3^{rd} Quintile^h	-0.012	-0.012	-0.038	-0.034	**-0.083**^{b}	**-0.159**^{a}	-0.099	-0.009
	(0.021)	(0.032)	(0.030)	(0.031)	(0.036)	(0.049)	(0.071)	(0.072)
5^{th} Quintile^h	**0.054**^{c}	0.003	0.059	0.029	**0.117**^{a}	**0.147**^{a}	**0.163**^{b}	0.058
	(0.028)	(0.046)	(0.039)	(0.040)	(0.035)	(0.047)	(0.064)	(0.070)
Obs.	97	31	32	33	33	33	33	33
Country	11	11	11	11	11	11	11	11
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ and time dummies								

Note: Robust standard errors in parenthesis. a, b and c are 1, 5 and 10 per cent significance level respectively.

Table 5
Human Capital and Growth in the Euro Area
Dependent variable: per capita income growth rate. System GMM
Robustness check: rule out one country at a time

	1980-1990		1985-1995		1990-2000	
	Gini^h	5^{th} Quintile^h	Gini^h	5^{th} Quintile^h	Gini^h	5^{th} Quintile^h
Austria	0.057^b	0.109^a	0.104^a	0.147^b	0.097^c	0.181^b
	(0.025)	(0.038)	(0.035)	(0.053)	(0.050)	(0.072)
Belgium	0.052^c	0.111^b	0.109^a	0.159^a	0.093^b	0.173^a
	(0.026)	(0.039)	(0.034)	(0.050)	(0.042)	(0.059)
Finland	0.060^b	0.124^a	0.095^a	0.127^a	0.105^b	0.182^b
	(0.027)	(0.038)	(0.031)	(0.044)	(0.049)	(0.068)
France	0.059^b	0.122^a	0.124^a	0.177^a	0.108^b	0.200^a
	(0.026)	(0.038)	(0.033)	(0.048)	(0.047)	(0.066)
Germany	0.065^b	0.123^a	0.113^a	0.150^a	0.090^c	0.168^b
	(0.025)	(0.036)	(0.034)	(0.049)	(0.049)	(0.070)
Greece	0.047^c	0.103^b	0.080^c	0.109^c	**-0.009**	**-0.008**
	(0.026)	(0.039)	(0.039)	(0.055)	(0.046)	(0.074)
Ireland	0.056^c	0.181^a	0.102^a	0.180^a	0.072^c	0.132^b
	(0.032)	(0.055)	(0.034)	(0.055)	(0.037)	(0.055)
Italy	0.057^b	0.096^a	0.132^a	0.140^b	0.127^b	0.178^b
	(0.022)	(0.028)	(0.042)	(0.050)	(0.058)	(0.072)
Netherlands	0.058^b	0.117^a	0.106^a	0.144^a	0.094^c	0.170^b
	(0.024)	(0.034)	(0.033)	(0.049)	(0.049)	(0.070)
Portugal	**0.059**	0.250^a	**0.011**	**-0.161**	**-0.154**	**-0.053**
	(0.048)	(0.081)	(0.067)	(0.162)	(0.114)	(0.267)
Spain	0.058^b	0.132^a	0.108^a	0.176^a	0.103^b	0.163^b
	(0.024)	(0.036)	(0.034)	(0.049)	(0.048)	(0.069)
Obs.	30	30	30	30	30	30
Countries	10	10	10	10	10	10
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ and time dummies						

Note: Robust standard errors in parenthesis. a, b and c are 1, 5 and 10 per cent significance level respectively.

Table 6

Income Inequality and Economic Growth

Dependent variable: per capita income growth rate. System GMM

LIS	$Gini^y$	90/10	90/50	80/20	Obs.	Countries
	(1)	(2)	(3)	(4)		
Advanced Economies						
1975-2005	**0.077**^{c}	0.003	0.017	**0.010**^{b}	80	17
	(0.046)	(0.002)	(0.011)	(0.005)		
1975-1990	-0.002	0.001	-0.003	0.002	31	14
	(0.053)	(0.003)	(0.014)	(0.006)		
1990-2005	0.079	0.002	0.018	**0.010**^{c}	62	17
	(0.051)	(0.002)	(0.012)	(0.006)		
European Countries						
1975-2005	0.055	0.001	0.014	0.097	69	16
	(0.051)	(0.002)	(0.010)	(0.064)		
1975-1990	-0.032	-0.006	-0.000	-0.011	23	12
	(0.088)	(0.006)	(0.020)	(0.014)		
1990-2005	0.076	0.003	**0.019**^{c}	**0.012**^{c}	57	16
	(0.053)	(0.003)	(0.011)	(0.006)		
Euro Area						
1975-2005	0.117	0.001	0.028	0.021	39	10
	(0.088)	(0.062)	(0.018)	(0.014)		
1975-1990						
1990-2005	0.071	-0.003	0.021	0.015	34	10
	(0.099)	(0.006)	(0.019)	(0.015)		

Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ *and time dummies*

Note: Robust standard errors in parenthesis. a, b and c are 1, 5 and 10 per cent significance level respectively.

TABLE A

INCOME GINI COEFFICIENTS FOR 56 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
Mauritania	-	-	-	-	-	0.491	0.444	0.468	0.033
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	52	45	56	56

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) .