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Inequality and growth in advanced economies: an empirical investigation

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Abstract This paper empirically investigates 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 and 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, both in the sample as a whole and in the low and middle-income economies, an effect that vanishes or becomes positive in the higher-income countries.

Keywords Human capital and income inequality · Economic growth · Dynamic panel data model

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, but the literature has not provided a conclusive answer so far. In the early nineties, theoretical models formalizing a negative effect of wealth inequality on economic growth attracted

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considerable attention because of the increased empirical support for their conclusions.[1] However, with the appearance of Deininger and Squire's [23] data set, panel data models challenged the negative effect of income inequality on growth found in cross-section regressions. Barro [10], for instance, finds little association between income inequality and economic growth in a broad panel of countries. In addition, he notes that the sign of the effect varies with per capita income, reporting a negative link in poor countries and a positive link in richer ones. Yet, the most surprising result is that of Forbes [27], who, by controlling for country-specific effects, provides evidence that in the medium and short-term, an increase in the level of inequality in the distribution of income in a country shows a positive and significant relationship with 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., [9]). Other papers object that income inequality data may be a poor proxy for wealth inequality, which is the source of inequality in most theoretical models. Accordingly, they focus on the distribution of assets, mainly land and human capital, to analyze the effect of inequality on growth (e.g., [3, 19, 22, 24]). Finally, Voitchovsky [47] states that previous empirical studies have used aggregate indicators of inequality—as measured, for example, by the Gini coefficient—which mask the differing effects of the lower and upper part of the income distribution on growth. And it is at this point that the debate in the empirical literature on the effects of inequality on growth now stands.

This paper reassesses the empirical relationship between inequality and economic growth by focusing on groups of countries with distinct income levels. It departs from the previous literature in the following ways. First, it analyzes whether the relationship between inequality and growth differs across regions with different levels of development, paying special attention to the high-income OECD countries. This exercise is informative because, according to Barro's [10] result, the effect of income inequality on economic growth may differ between 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. As a result, mixing countries at different stages of development in the same pool may give misleading conclusions.

Second, this paper distinguishes between assets and income inequality. In addition to the standard income inequality measures, it makes use of available data on human

[1] Part of this literature focused on the political economy 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 favors more redistribution, will experience lower growth rates [3, 13, 42]. Other studies argued that under the presence of imperfect credit markets, poor individuals with no collateral will be unlikely to undertake a profitable investment project, which implies that the greater the number of restricted individuals, the lower the average investment rate in the society [29]. See Benabou [12], Perotti [41], Aghion et al. [1] and García-Peñalosa [30] for a comprehensive survey of this literature.

[2] Also estimating a dynamic panel data model but using regional data from different US states, Panizza [40] 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, but depends on the econometric specification and the method used to measure inequality.

capital inequality for a broad number of countries and periods. The advantage of human capital inequality data is that they are less subject to limitations regarding comparability across countries than income inequality measures.[3] Moreover, they are available for all regions of the world, covering a total of 108 countries for the period 1960 to 2000. The disadvantage, however, is that results cannot be interpreted as evidence for or against theoretical models in which wealth is measured in a broader sense and mainly affects the investment of physical capital (e.g., the political economy mechanism); they can only be interpreted in relation to those models in which human capital inequality is relevant. From a theoretical perspective, the latest advances in the literature have pointed to human capital inequality and its influence on demographic variables as alternative channels that predict a negative relationship between inequality and growth. Castelló-Climent and Doménech [20] 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 [21] and Moav [38]. Furthermore, the role of human capital inequality in economic growth is part of most of the models that analyze the effect of inequality on growth under imperfect credit markets (e.g., [29, 39]).[4]

Methodologically, this paper uses the system GMM estimator to control for country-specific effects. The reason is that the traditional first difference GMM estimator used by Forbes [27] may not be appropriate when variables are highly persistent, as is the case with income and education inequality measures. For example, in a sample that includes all regions of the world, more than 90% of the variation in income and human capital inequality measures is cross-sectional, whereas the explanatory power of time dummies in regressions in which the dependent variables are the Gini coefficients for income or human capital is less than 1%. Thus, by taking first differences, most of the variation in the data, which comes from variability across countries, disappears. This paper accounts for these problems by using the system GMM estimator, which has been proven to perform better than the first difference GMM estimator when variables are highly persistent (e.g., [15]).[5]

Interestingly, using an updated version of the Deininger and Squire [23] data set, our results show a negative and statistically significant coefficient for the income Gini index in the estimation of a conventional growth equation, suggesting that the influential results by Forbes [27] are not robust to an econometric technique that in addition to controlling for country-specific effects also takes into account the persistency of inequality measures. It is also found that the effect of income inequality on economic growth differs across country income groups. In line with

[3]Note, however, that the measures of education refer to the quantity of schooling, which do not take into account the quality of the educational system. Thus, they do not capture the fact that a year of French and a year of Kenyan education is not the same.

[4]A comprehensive empirical analysis of the channels through which human capital inequality may influence human capital accumulation and growth rates is examined by Castello-Climent [18]. By estimating the structural form of the model, the findings reveal that, all other things being equal, a greater degree of human capital inequality increases fertility rates and reduces life expectancy, which in turn discourages the accumulation of human capital. Moreover, the adverse effect of human capital inequality on investment and growth is reinforced when individuals find it difficult to gain access to credit.

[5]For the use of the system GMM estimator in growth equations see, for example, Bond et al. [16], Dollar and Kraay [25] and Voitchovsky [47], among others.

Barro [10], the negative influence of a more unequal distribution of income on growth in low and middle-income countries becomes positive in the high-income OECD and European economies. The positive influence of income inequality on growth in wealthy economies is also confirmed by the high-quality data set taken from the Luxemburg Income Study [37], which suggests the effect to be stronger during the period 1990–2005 than during the years 1975–1990.

With regard to human capital inequality, results also show a different effect on growth depending on the level of development of the countries. Findings reveal that a greater degree of human capital inequality discouraged the per capita income growth rates in most parts of the world during the period 1965–2005. This was especially true in the developing countries, where the life expectancy and fertility channels seem to play a prominent role. In contrast, the negative effect vanishes in higher-income economies. Moreover, to rule out that the human capital inequality measure is picking up an income inequality effect both inequality indicators are entered in the set of controls. When the joint effect is analyzed, the results scarcely change; the negative effect of human capital inequality on growth holds in the low and middle-income countries, whereas income inequality continues having a positive influence in wealthy economies, which suggests that the findings are not driven by the correlation between the two inequality indicators.[6]

The demographic mechanisms (e.g., [21] and [20]) and credit market constrains (e.g., [29]) are plausible explanations of why human capital inequality may be harmful for growth, as shown by Castelló-Climent [18], particularly in developing countries, where fertility rates are higher, life expectancy is lower and the presence of credit market constraints is more generalized throughout the financial system. At lower levels of development, the negative influence of income inequality on growth might also be explained by a greater prevalence of political instability and social unrest (e.g. [2]).

Whereas the literature has focused mainly on those models in which inequality is harmful to growth, there are some theoretical explanations of why income inequality may have a beneficial effect. The classical approach [34] states that the marginal propensity of the rich to save is higher than that of the poor; therefore, higher inequality may promote economic growth as it increases available savings and investment. Another explanation could be that in an economy in which a median voter chooses taxes to finance the provision of public education, higher income inequality may encourage growth by increasing human capital accumulation [43]. Moreover, income inequality may also raise the incentives for investment in an economy with heterogeneity in ability. For instance, during periods of major technological inventions, the relative importance of ability with regard to initial parental conditions increases, which causes intergenerational mobility and income inequality to increase. At the same time, the concentration of high-ability workers in technologically advanced sectors promotes future technological progress and stimulates growth (e.g., [28] and [33]).

The organization of the paper is as follows. The next Section discusses the data and the econometric model to be estimated. Section 3 displays the results about the influence of income and human capital inequality on economic growth in

[6] Along a similar line, Deininger and Olinto [22] also show that income and land inequality affect growth through different channels.

different groups of countries that include low and middle-income as well as wealthy economies. Section 4 focuses on the high-income economies and analyzes the effect of inequality on growth in more detail by using better quality data for income inequality measures taken from the Luxemburg Income Study [37] data set. Finally, 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-sectional 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 this kind of regression is that they suffer from two sources of inconsistency. On the one hand, cross-sectional estimates fail to control for specific country characteristics, 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 properly address the treatment of some explanatory variables that, according to the theory, should be considered endogenous. Both remarks appear to be extremely important in the relationship between income inequality and economic growth, as suggested by Forbes's [27] results.[7] Therefore, we propose to analyze the effect of income and human capital inequality on economic growth by estimating the following standard growth equation:

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

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 5-year span, $Inequality_{i,t-\tau}$ measures income or human capital inequality in country i lagged 5 years, 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., [10]).[8]

Reorganizing, we can rewrite Eq. 1 as a dynamic model:

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

[7] Perotti [41] and Castelló and Doménech [19] find that even the negative effect of income inequality on growth in cross-section regressions is sensitive to the inclusion of region-specific dummies, pointing to an omitted variable bias.

[8] 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. Nevertheless, in this study, the accumulation of human and physical capital are excluded from the set of controls because they are endogenous in the model since most of the mechanisms that predict a negative effect of inequality on growth work through a discouraging effect on the investment rates. However, we will analyze the robustness of the results to the inclusion of the investment rates in the model.

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 most common approach used to estimate dynamic panel data models is the first-difference Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond [5]. The idea of this estimator is to take first differences to eliminate the source of inconsistency and use the levels of the explanatory variables lagged two and further periods as instruments. However, although the first-difference GMM estimator deals properly with the problem of unobservable heterogeneity, it has some shortcomings in the estimation of Eq. 2. The first has to do 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, whereas the explanatory power of country dummies in regressions where the dependent variable is the income or the human capital Gini coefficient is more than 90%, the explanatory power of time dummies in similar regressions is less than 1%. 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 [31]. Moreover, some studies have pointed out that when explanatory variables are persistent, the lagged levels of the explanatory variables are weak instruments for the variables in differences.[9]

A solution to these problems comes from Arellano and Bover [6] and Blundell and Bond [15], who develop an estimator that makes use of further moment conditions. Specifically, the system GMM estimator, in addition to using the variables lagged two and further periods as instruments in the first-difference equation, also uses the information provided by lagged differences to instrument an equation in levels.

The system of dynamic equations to be estimated is as follows:

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

$$\ln y_{i,t} = \widetilde{\beta} \ln y_{i,t-\tau} + \widetilde{\gamma} Inequality_{i,t-\tau} + X_{i,t-\tau}\widetilde{\delta} + \widetilde{\xi}_t + \widetilde{\alpha}_i + \widetilde{\varepsilon}_{i,t} \tag{4}$$

The first-difference GMM estimator only considers the first equation. The main idea of the difference estimator is to remove the source of inconsistency (α_i) by taking first differences. However, Eq. 3 introduces by construction a new problem since the transformed error term ($\widetilde{\varepsilon}_{i,t} - \widetilde{\varepsilon}_{i,t-\tau}$) is correlated with the lagged dependent variable [E($\ln y_{i,t-\tau}\ \ \varepsilon_{i,t-\tau}$) $\neq 0$]. Nevertheless, under the assumption that the error term is not second order serially correlated, we can estimate the above system of equations by the GMM estimator using the following moment conditions:

$$E[(\widetilde{\varepsilon}_{i,t} - \widetilde{\varepsilon}_{i,t-\tau})W_{i,t-s\tau}] = 0 \text{ with } s \geq 2 \tag{5}$$

where $W = [\ln y\ \ Inequality\ \ X]$. We are assuming that the explanatory variables are weakly exogenous, that is, the explanatory variables are uncorrelated with future

[9] Alonso-Borrego and Arellano [4] show that the shortcomings of weak instruments translate into large finite sample bias.

realizations of the error term. These identifying assumptions imply that for Eq. 3, we can use $W_{i,t-2\tau}$ and all further lags as instruments for the explanatory variables in differences.

The system GMM estimator is a combination of the above moment conditions for the equations in first differences, together with additional moment conditions for the equations in levels. In particular, the instruments for the equations in levels are 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 assumed to be constant over time. The additional moment conditions for the equations in levels are:

$$E[(\Delta W_{i,t-s\tau}(\widetilde{\alpha}_i + \widetilde{\varepsilon}_{i,t})] = 0 \text{ with } s = 1 \tag{6}$$

If the moment conditions are valid, Blundell and Bond [15] show that in Monte Carlo simulations, the system GMM estimator performs better than the first-difference counterpart. We can test the validity of the moment conditions by using the conventional test of overidentifying restrictions proposed by Sargan [44] and Hansen [32] 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-in-Sargan test.

The use of the system GMM estimator will allow us not only to provide efficient and consistent estimators for the persistent inequality indicators, but also to check whether the contrasting positive relationship between income inequality and economic growth found with the first-differences GMM estimators is robust to the use of the system GMM.

2.2 Data

The income Gini coefficient ($Gini^y$) used in the first part of the paper is taken from the UNU/WIDER-UNDP World Income Inequality Database (WIID) version 1.0, which is an updated version of Deininger and Squire's [23] data set and reports income inequality measures for developed as well as developing economies. Under the same premise of including only "high quality" data, we broaden the observations used by Forbes [27] 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 [27] and the new sample used in this study are displayed in Table A1 in "Appendix".[10] Although we can include only twelve more countries, Table A1 in "Appendix" shows that most of them are developing countries and

[10]To deal with inconsistencies in the definition of income inequality measures, we follow Deininger and Squire [24], Li and Zou [36], Forbes [27], and Banerjee and Duflo [9] and add 0.066 points to the Gini coefficient based on expenditure data to transform it into an income-based Gini, which is the average difference observed by Deininger and Squire between both definitions.

six are in Africa.[11] This enlargement goes 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 are a total of 56 countries with at least two observations of the income Gini index.

However, Atkinson and Brandolini [8] have warned about the measurement error in cross-country regressions when using income inequality data. In fact, the authors show that even the high-quality data of Deininger and Squire [23] for OECD countries contain problems since definitions and data collection methods differ across countries.[12] Thus, in the second part of the paper, in which we focus on the effect of inequality on growth in a sample of economically advanced economies and European countries, we use the Luxemburg Income Study (LIS) [37], version June 2007, which provides improved data for income inequality measures in terms of their quality and comparability across countries. The Gini coefficients from the LIS data set for 23 countries from 1970 to 2000 are also reported in Table A1 in "Appendix". In addition to the income Gini coefficient ($Gini^y$), the data set also provides information on different parts of the distribution such as the *90\10*, *90\50* and *80\20* percentile ratios. These measures express the ratio of household incomes, adjusted by equivalence scale, at various percentile points on the income scale. For example, the *90\10* percentile ratio shows the share of income owned by the richest 10% in a country with respect to the share owned by the poorest 10%.

Nevertheless, in spite of the advantages in terms of quality and comparability of the data across countries, the main drawback of the LIS data set is that it only contains data for a reduced sample of wealthy economies starting mainly in 1980, which reduces the sample size considerably. A more comprehensive data set on inequality measures is that for human capital inequality variables, which is available for 108 countries during the period 1960–2000. The data include the human capital Gini coefficient ($Gini^h$) and the distribution of education by quintiles ($Quintile^h$), computed by Castelló and Doménech [19]. These variables are calculated using information on attainment levels and the average schooling years of the total population aged 25 years and above, taken from Barro and Lee [11].

The remaining data used include standard determinants of the growth rates. The 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.[13] 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 [26]. Finally, the stock of human capital (*Educ*) is measured as the average years

[11] Table A1 in "Appendix" reports data on 12 countries that were not included in Forbes' sample. These countries are Algeria, Iran, Israel, Jordan, Ghana, Mauritania, Mauritius, South Africa, Uganda, Honduras, Jamaica, and Taiwan. However, unlike Forbes' study, Table A1 in "Appendix" does not report data on Bulgaria because this country is not included in Castello and Domenech's [19] data set.

[12] For problems related to income inequality measures see also Székely and Hilgert [45] and Knowles [35].

[13] The latest version of the PWT has updated the measures of per capita income up to 2005.

of secondary and higher education in the male population aged 25 years and above taken from the latest Barro and Lee [11] data set.[14]

3 Empirical results

We start by analyzing the effect of human capital inequality on economic growth in a broad sample that includes 102 countries. From a theoretical perspective, 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.

In line with the empirical literature, we start the analysis of the effect of human capital inequality on growth using the Gini coefficient, which is an aggregate measure of inequality. The results, displayed in Table 1, show a clear negative and statistically significant effect of the human capital Gini coefficient on the per capita income growth rates in a sample that includes all countries in the world for which there are available data. This effect is not only statistically significant at the 1% level but also considerable in quantitative terms; an increase in 0.1 points in the human capital Gini index reduces the annual growth rate by 0.50%. 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 by the share of total trade, has a positive influence on a country's per capita income growth rate, whereas more inflation has a negative one.

In order to test whether this effect differs in countries with different levels of development, columns (2–6) address the influence of human capital inequality on growth in different regions of the world.[15] The results show that the estimated coefficient in the whole sample holds virtually unchanged when we reduce the countries to include only low and middle-income economies. Likewise, when we restrict the sample to high-income and OECD countries, the estimated coefficient of the human capital Gini index continues having a negative and statistically significant impact at the 1% level, though it is smaller in absolute value.

Nevertheless, given that there are economies with different income levels in the group of OECD countries and that the high-income group includes countries such as Barbados, Trinidad and Tobago, Bahrain, and Kuwait, among others, column (5) contains only those countries that belong to the OECD and that are classified as high-income economies—we will use the term "advanced economies" to describe this group. Interestingly, the results show that the estimated coefficient of the Gini index is reduced by more than half and stops being statistically significant. Moreover, the absence of a negative effect from human capital inequality on growth is even clearer

[14] Evidence suggests that higher male levels of education account more for growth than primary and female education (see, for example, Barro [10]).

[15] Table A2 in the "Appendix" lists the countries included in each group. The income classification is taken from the World Bank in 2007, which divides economies into income groups according to 2006 per capita gross national income (GNI). Low and middle-income countries are those with $11,115 or less.

Table 1 Human capital inequality and economic growth in different groups of countries. Dependent variable: per capita income growth rate

	World	Low & Middle income	High income	OECD	Advanced	Europe	World	Low & Middle income	High income	OECD	Advanced	Europe
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Gini^{h}_{t-\tau}$	−0.050[a]	−0.048[a]	−0.039[a]	−0.034[a]	−0.015	−0.005	0.008	0.010	0.004	−0.000	−0.024	−0.011
	(0.015)	(0.017)	(0.013)	(0.011)	(0.014)	(0.015)	(0.013)	(0.015)	(0.014)	(0.011)	(0.015)	(0.017)
$lny_{t-\tau}$	−0.006[a]	−0.005[a]	−0.049[a]	−0.025[a]	−0.034[a]	−0.029[a]	−0.018[a]	−0.011[a]	−0.049[a]	−0.039[a]	−0.038[a]	−0.029[a]
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$Educ_{t-\tau}$	0.002	−0.000	0.004[a]	0.002[c]	0.001	0.001	−0.003	−0.006	0.001[a]	0.003[a]	0.002	0.001
	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.000)	(0.001)	(0.001)	(0.001)
$(G/GDP)_{t-\tau}$	−0.037	−0.033	0.018	−0.052[b]	−0.063[a]	−0.036	−0.031	−0.040	0.022	−0.053[b]	−0.060[a]	−0.036
	(0.026)	(0.028)	(0.023)	(0.025)	(0.022)	(0.022)	(0.025)	(0.028)	(0.021)	(0.022)	(0.022)	(0.023)
$Trade_{t-\tau}$	0.010[a]	0.013[a]	0.008[a]	0.011[a]	0.008[b]	0.011[a]	0.005[c]	0.009[b]	0.010[a]	0.012[a]	0.008[b]	0.011[a]
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)
$Inflation_{t-\tau}$	−0.002[a]	−0.002[a]	−0.008	−0.035[a]	−0.026	−0.011	−0.002[a]	−0.002[a]	−0.002	−0.030[a]	−0.012	−0.003
	(0.000)	(0.000)	(0.010)	(0.007)	(0.019)	(0.018)	(0.000)	(0.000)	(0.009)	(0.006)	(0.020)	(0.020)
$lnFERT_{t-\tau}$							−0.040[a]	−0.043[a]	−0.015[b]	−0.012[a]	−0.012[b]	−0.005
							(0.007)	(0.009)	(0.006)	(0.004)	(0.006)	(0.006)
$lnLE_{t-\tau}$							0.047[a]	0.034[c]	0.130[b]	0.129[a]	0.014	−0.024
							(0.018)	(0.020)	(0.052)	(0.036)	(0.050)	(0.062)
Constant	0.105[a]	0.086[c]	0.477[a]	0.279[a]	0.359[a]	0.309[a]	0.049	0.052	0.065	−0.145	0.347[c]	0.417[c]
	(0.038)	(0.047)	(0.035)	(0.030)	(0.032)	(0.047)	(0.074)	(0.887)	(0.204)	(0.133)	(0.186)	(0.242)
Countries	102	70	32	27	23	17	101	70	31	27	23	17
Obs	744	474	270	236	204	151	732	470	262	236	204	151
AR (2) test	[0.129]	[0.117]	[0.875]	[0.558]	[0.094]	[0.354]	[0.171]	[0.139]	[0.848]	[0.605]	[0.011]	[0.350]
Sargan test	[0.001]	[0.001]	[0.083]	[0.209]	[0.444]	[0.988]	[0.001]	[0.005]	[0.253]	[0.782]	[0.981]	[0.999]
Diff Sargan	[0.029]	[0.597]	[0.996]	[1.000]	[0.999]	[1.000]	[0.270]	[0.457]	[1.000]	[1.000]	[0.999]	[1.000]

Note: Standard errors in parenthesis. The period of analysis is 1965–2005. The set of controls also include period dummies. 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

[a]1% significance level

[b]5% significance level

[c]10% significance level

in the reduced sample of European economies, where the estimated coefficient of the human capital Gini index is closer to zero.[16]

One possible explanation for the differing effects of human capital inequality on growth in low and middle-income countries and in the advanced economies is that differences in fertility and life expectancy among individuals are more pronounced in less developed 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 fertility rates and a measure of life expectancy in the set of controls. In line with the theoretical predictions, columns (7–12) show that once demographic variables are included in the set of controls, the negative and statistically significant coefficient of the human capital Gini index disappears. Furthermore, results suggest that longer life expectancy and lower fertility rates have a positive influence on the growth rates of per capita income in all groups of countries except in the advanced and European economies.

Overall, these results indicate that the effect of human capital inequality on economic growth differs according to the level of economic development in a country. Whereas in low and middle-income countries human capital inequality has a negative impact on the per capita income growth rates, mainly through its effect on demographic variables, in more economically advanced economies, this impact is non-existent.

To verify whether human capital inequality is picking up an income inequality effect, Table 2 examines the individual and joint effects of income and human capital inequality on the per capita income growth rates in different regions of the world. In the first place, given that by controlling for income inequality the number of available countries is cut in half and that in many of these countries there are only data for two consecutive periods, we check whether the results in Table 1 hold in the reduced sample of 56 countries, for which there are data available on income inequality measures. Then we analyze the independent and joint effects of income and human capital inequality on economic growth.

In line with the previous findings, the results concerning human capital inequality hold in the reduced sample of countries for which data are available for income inequality measures; the estimated coefficient of the human capital Gini index is negative and statistically significant in all samples but in the groups of wealthier economies, in which the effect is not significant.[17]

[16]We check the robustness of the results by measuring the stock of human capital with the average years of secondary and tertiary education of the total population instead of that of the male population. The idea is that over the last decades economies have experienced a greater participation of women in education. As a result, our measure of the stock of human capital may understate real changes in average human capital and influence the coefficient of the human capital Gini index. However, when using the broader definition for the stock of human capital the results scarcely change. For instance, the estimated coefficient of the Gini index (and standard deviation) for the world (−0.048 (0.014)), low and middle-income (−0.046 (0.017)), high-income (−0.037 (0.013)), OECD (−0.033 (0.012)), advanced (−0.013 (0.014)) and European (−0.003 (0.015)) countries are similar to those reported in Table 1.

[17]To compare the different results obtained in Tables 1 and 2 for the high-income countries, in Table 1 we remove one country at a time for which no data on income inequality are available (Barbados, Bahrain, Kuwait, Cyprus, Austria, Iceland, and Switzerland). Our results clearly show that the negative coefficient of the human capital Gini index found in Table 1 in the high-income group disappears once Kuwait is removed from the sample.

Table 2 Human capital inequality, income inequality and economic growth. Dependent variable: per capita income growth rate

	World			Low & Middle income			High income			OECD			Advanced			Europe		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$Gini^h_{t-\tau}$	−0.028[c]		−0.025[c]	−0.036[b]		−0.036[b]	0.026		0.027	−0.031[b]		−0.022	−0.011		−0.011	−0.003		−0.011
	(0.015)		(0.015)	(0.014)		(0.015)	(0.023)		(0.031)	(0.014)		(0.016)	(0.021)		(0.021)	(0.027)		(0.022)
$Gini^y_{t-\tau}$		−0.053[c]	−0.061[b]		−0.017	0.000		−0.025	−0.026		−0.042[b]	−0.028		0.038	0.038		0.060[b]	0.063[b]
		(0.027)	(0.025)		(0.026)	(0.024)		(0.031)	(0.031)		(0.021)	(0.023)		(0.028)	(0.028)		(0.029)	(0.030)
Countries	56	56	56	31	31	31	25	25	25	24	24	24	20	20	20	14	14	14
Obs	244	244	244	119	119	119	125	125	125	125	125	125	104	104	104	69	69	69
AR (2)	[0.076]	[0.079]	[0.064]	[0.046]	[0.042]	[0.098]	[0.212]	[0.214]	[0.230]	[0.912]	[0.992]	[0.968]	[0.954]	[0.979]	[0.954]	[0.690]	[0.598]	[0.644]
Sargan test	[0.045]	[0.121]	[0.115]	[0.773]	[0.709]	[0.852]	[0.826]	[0.826]	[0.961]	[0.857]	[0.857]	[0.961]	[0.969]	[0.969]	[0.989]	[0.995]	[0.995]	[0.999]
Diff Sargan	[0.879]	[0.977]	[0.967]	[0.986]	[0.948]	[0.998]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.999]	[0.999]	[0.999]	[1.000]	[1.000]	[1.000]

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

Controlling for physical capital investment																		
$Gini^h_{t-\tau}$	−0.028[b]		−0.026[b]	−0.031[b]		−0.032[b]	0.029		0.030	−0.015		−0.009	−0.021		−0.008	−0.006		−0.013
	(0.013)		(0.012)	(0.013)		(0.014)	(0.022)		(0.022)	(0.013)		(0.015)	(0.057)		(0.021)	(0.022)		(0.022)
$Gini^y_{t-\tau}$		−0.065[a]	−0.050[b]		−0.013	0.001		−0.036	−0.038		−0.026	−0.020		0.022	0.022		0.051[c]	0.054[c]
		(0.022)	(0.020)		(0.025)	(0.024)		(0.031)	(0.031)		(0.019)	(0.021)		(0.028)	(0.028)		(0.030)	(0.031)
Countries	56	56	56	31	31	31	25	25	25	24	24	24	20	20	20	14	14	14
Obs	244	244	244	119	119	119	125	125	125	125	125	125	104	104	104	69	69	69
AR (2)	[0.088]	[0.093]	[0.076]	[0.098]	[0.059]	[0.033]	[0.214]	[0.249]	[0.240]	[0.992]	[0.962]	[0.975]	[0.805]	[0.849]	[0.864]	[0.551]	[0.554]	[0.548]
Sargan test	[0.180]	[0.217]	[0.407]	[0.817]	[0.817]	[0.933]	[0.966]	[0.966]	[0.986]	[0.966]	[0.966]	[0.986]	[0.991]	[0.991]	[0.997]	[0.999]	[0.999]	[1.000]
Diff Sargan	[0.998]	[0.991]	[0.999]	[0.986]	[0.988]	[0.998]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$, $lns^k_{t-\tau}$ and *time dummies*																		

Note: Standard errors in parenthesis. The period of analysis is 1970–2000. The source of income inequality is United Nations World Income Inequality Database, WIID [46]

[a] 1% significance level

[b] 5% significance level

[c] 10% significance level

The second column of every group of countries reports the effect of income inequality on economic growth, measured with the income Gini coefficient taken from WIID. Column (2) shows that income inequality hampers per capita income growth in the whole sample, which includes all countries for which data are available; the estimated coefficient is negative and statistically significant. This result is remarkable because it highlights that the opposite findings of Forbes are not robust to the use of the system GMM estimator. A plausible explanation is that Forbes' results are influenced by the high persistence and measurement error in the inequality measures, exacerbated by the use of the first-difference GMM estimator.

As in the case of human capital inequality, our results also suggest that the influence of income inequality on economic growth differs across country income groups. In fact, the negative coefficient found in the low and middle-income, high-income, and OECD countries reverses sign and becomes positive in the advanced and European countries. The positive influence is only statistically significant, however, in the European region.

The third column of each group of countries includes both human capital and income inequality in the set of controls. Column (3) shows that the estimated coefficient of the income and human capital inequality indicators changes slightly and continues to be statistically significant when both measures are included in the set of controls, indicating that income and human capital inequality have a negative and independent effect on per capita income growth rates. Moreover, the negative effect of human capital inequality on growth holds in the low and middle-income countries, whereas the income Gini index continues being positive and statistically significant in the European economies, which suggests that previous results were not driven by the correlation between income and human capital inequality.[18]

Whereas the impact of human capital inequality on growth is more likely to be mediated by the human capital investment rates (see [21], and [20]), some theories suggest that wealth and income inequality hamper per capita income growth rates by discouraging physical capital investment (e.g., the credit market imperfection approach, the political economy mechanism, and the social unrest channel). Thus, it is also interesting to see how sensitive the results are to the inclusion of physical capital investment rates in the model. Our findings, reported at the bottom of Table 2, show that with the exception of the OECD economies, controlling for physical capital investment rates scarcely changes the results, which indicates that income inequality has an independent effect on growth that differs from its effect on investment. That is, income inequality affects growth not only through investment rates but also through the efficiency of resource use.

In summary, when human capital and income inequality are both included in the set of controls, the results point to a negative effect of greater inequality in the distribution of income and human capital on per capita income growth in the whole sample. However, when the sample is split into groups of countries according to their level of development, the results differ somewhat. With regard to human capital inequality, the estimated coefficient of the Gini index is negative in almost all groups

[18]The simple correlation between the income (WIID data set) and human capital Gini coefficient is not very high. For example, the correlation is 0.379 for the whole sample, 0.056 for the low and middle-income countries, 0.207 for the high-income countries, 0.156 for the advanced economies, and 0.355 for the European countries.

of countries, although it is only statistically significant in the low and middle-income economies, an effect that is mainly explained through the demographic channels. On the other hand, the negative effect of income inequality on growth becomes positive in the group of advanced and European economies, an effect that even holds when controlling for the physical capital investment rates.

4 Income and human capital inequality in the advanced economies

This section examines 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, using the high-quality comparable LIS data set to measure income inequality.

Figure 1 plots the evolution of the income Gini coefficient for the advanced economies over the period 1970–2000.[19] For the few countries for which data are available on the seventies, we observe a general 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 and Sweden. However, the behavior 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 greatest increase is found in the United States, the United Kingdom, Australia, and Sweden. The tendency of increasing income inequality continues during the nineties as well. Some exceptions are Denmark, the Netherlands, France, Switzerland, Ireland, and Greece, which slightly reduced income inequality over this period. However, in spite of the general increase in income inequality in the advanced economies since 1980, in the year 2000, we see noticeable differences in income inequality among these countries. Specifically, income Gini coefficients above 0.33 can be found in the United States, the United Kingdom, Spain, and Greece. On the other extreme are Denmark, the Netherlands, Finland, Norway, and Sweden, with income Gini coefficients below 0.26.

The patterns of human capital inequality, however, differ from those observed for income inequality. Broadly, human capital inequality has remained constant over the whole period. In fact, Fig. 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 for income inequality. For instance, in the year 2000, Portugal and Italy displayed a human capital Gini coefficient close to 0.4 and 0.35, respectively. On the other extreme were 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.[20] Another interesting remark is that countries with the greatest inequality in the distribution of income do not

[19]For a comprehensive study of the evolution of the income distribution over the twentieth century in a selection of wealthy economies, see Atkinson [7].

[20]The statistics for the advanced economies in the 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.

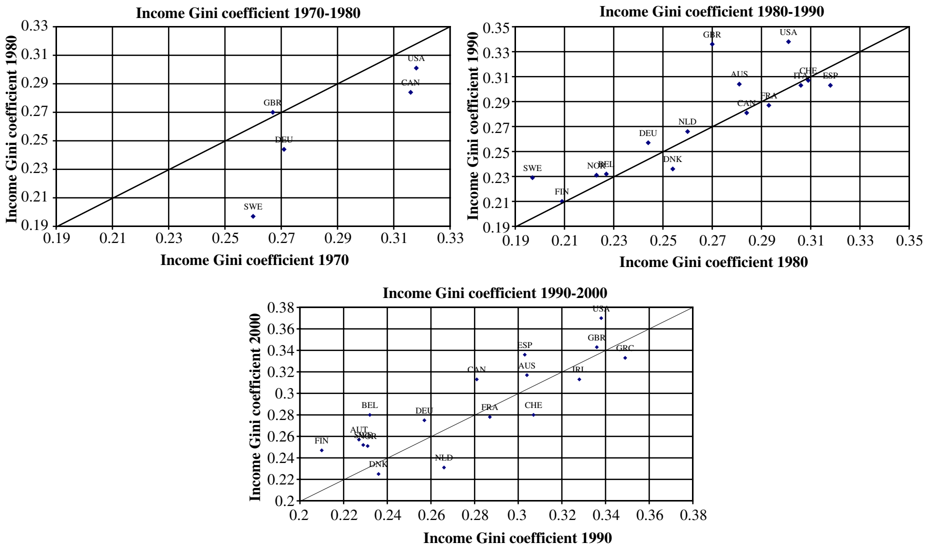

Fig. 1 Income Gini coefficient 1970–2000, LIS database

coincide with the countries with the greatest inequality in the distribution of human capital. For example, in the sample of advanced economies, the United States is the country with the highest income Gini coefficient and one of those with the lowest human capital inequality. In fact, the correlation between the human capital and the income Gini (LIS data set) coefficients for the advanced economies is very low: 0.068.

Since the evolution of inequality shows different patterns over the whole period, we first examine whether the effect of inequality on growth has remained stable

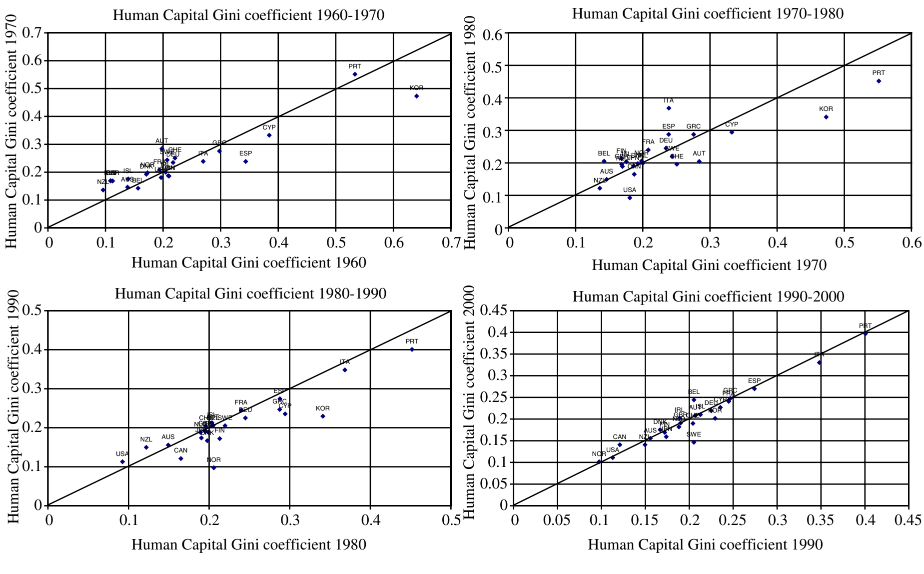

Fig. 2 Human capital Gini coefficient 1960–2000, Castelló and Doménech (2002) [19] database

Table 3 Human capital inequality and economic growth. Dependent variable: per capita income growth rate

	$Gini^h$	1^{st} $Quintile^h$	3^{rd} $Quintile^h$	5^{th} $Quintile^h$	$1^{st}Quintile^h$/ $5^{th}Quintile^h$	Obs.	Countries
	(1)	(2)	(3)	(4)	(5)		
Whole sample							
1965–2005	−0.050[a]	0.012	0.080[a]	−0.037[a]	−0.003	744	102
	(0.015)	(0.058)	(0.019)	(0.013)	(0.016)		
1965–1985	−0.100[a]	0.125	0.141[a]	−0.065[a]	0.029	393	95
	(0.024)	(0.097)	(0.032)	(0.020)	(0.026)		
1985–2005	−0.027	−0.177[c]	0.034	−0.018	−0.052[c]	445	101
	(0.023)	(0.096)	(0.029)	(0.022)	(0.029)		
Advanced countries							
1965–2005	−0.015	0.041	0.015	−0.016	0.009	204	23
	(0.014)	(0.028)	(0.018)	(0.024)	(0.008)		
1965–1985	−0.015	0.031	−0.002	−0.038	0.004	112	23
	(0.020)	(0.042)	(0.027)	(0.035)	(0.013)		
1985–2005	−0.027	0.064	0.032	−0.023	0.021[c]	115	23
	(0.023)	(0.042)	(0.032)	(0.034)	(0.011)		
European countries							
1965–2005	−0.005	0.001	0.011	−0.003	0.002	151	17
	(0.015)	(0.036)	(0.020)	(0.026)	(0.009)		
1965–1985	0.003	−0.020	−0.006	−0.013	−0.009	83	17
	(0.020)	(0.045)	(0.025)	(0.036)	(0.014)		
1985–2005	−0.028	0.052	0.039	−0.019	0.020	85	17
	(0.025)	(0.044)	(0.036)	(0.037)	(0.013)		
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ and *time dummies*							

Note: Standard errors in parenthesis
[a]1% significance level
[b]5% significance level
[c]10% significance level

over time or if it has changed over the years. In addition, we complement the information provided by the Gini coefficient with 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 does not provide any information on whether the lower an upper part of the distribution have different effects on the growth rates.[21]

Table 3 displays the results of the effect of human capital inequality on economic growth in the whole sample, advanced and European countries.[22] The controls include standard determinants of growth and time dummies, in line with the previous

[21]Using the LIS data set, Voitchovsky [47] finds 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.

[22]Bertola [14] finds that, compared to the EU15 countries, the European Monetary Union (EMU) seems to have improved the economic performance of the countries belonging to the euro area while also raising their income inequality and lowering their social spending. When we compare the effect of inequality on growth in the group of countries that belong to the EMU with that of the European countries that do not, we do not find any significant difference between the two groups.

tables. However, to save space, only the estimated coefficients for the inequality indicators are reported. In these regressions, the inequality indicators are included in the equation one at a time. The first row in every group of countries shows the results for the whole period, 1965–2005, and in the second and third row, the whole period is split into sub-periods of equal length, 1965–1985, and 1985–2005, to test whether the effect of human capital inequality differs over time.

The upper part of Table 3 provides evidence for the sample of all available countries. Results show that the negative influence of human capital inequality on per capita income growth rates, reported by the Gini coefficient in column (1), is also found with measures of the education distribution by quintiles. Columns (2–5) show that whereas a greater share of education in the hands of the middle-income group of the population (*3rd quintile*) had a beneficial effect on growth, a greater concentration of education in the upper part of the distribution (top 20%) discouraged growth. These effects are stronger during the period 1965–1985 than during the period 1985–2005. In fact, the estimated coefficients of the Gini index, third and fifth quintiles are not significant for the years 1985–2005. However, a greater share of education in the lowest 20% of the population had a detrimental effect on growth in recent years; the estimated coefficients of the first quintile and the ratio of the bottom to the top quintile are negative and statistically significant at the 10% level during the period 1985–2005.[23]

In line with the results reported in Table 1, when it comes to the advanced and European economies, the estimated coefficient of almost any inequality indicator is statistically not significant, suggesting no effect of human capital inequality on growth in this group of countries.

As for the effect of income inequality on economic growth, the stability of such an influence over time is analyzed with the high-quality LIS data set. 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 over a long time span. For example, for most of the countries, the first observation starts in 1980 and there is no information on income inequality for some countries included in the group of advanced economies such as Japan, Korea, Portugal, and New Zealand.

The results, displayed in Table 4, show a negative effect of income inequality on growth in the whole sample, which includes 23 countries. Among the percentile ratios, this result is reflected mainly in a negative and statistically significant coefficient of the ratio between the income of the 10% of individuals with the highest income and that of the 10% with the lowest income. Also in line with the previous results, income inequality seems to have a positive influence in wealthy economies. Not only the income Gini coefficient but also the percentile ratios show a positive and statistically significant effect on the growth rates of the advanced economies, an effect that is stronger towards the end of the sample period, 1990–2005. In addition, the estimated coefficients for the European countries are similar to those found for the advanced economies, although the estimated coefficients are almost never statistically significant.

[23]Since in many countries, more than 20% of the population are illiterate and therefore have zero years of schooling, we are forced to compute the ratio between the bottom to the top quintile instead of the fifth quintile/first quintile, which has been common when measuring income inequality.

Table 4 Income inequality and economic growth. Dependent variable: per capita income growth rate

LIS	Gini^y	90/10	90/50	80/20	Obs.	Countries
	(1)	(2)	(3)	(4)		
Whole sample						
1975–2005	−0.026	−0.002^c	−0.007	−0.003	104	23
	(0.033)	(0.001)	(0.006)	(0.003)		
1975–1990	−0.015	−0.002	−0.009	−0.005	39	19
	(0.061)	(0.002)	(0.011)	(0.006)		
1990–2005	−0.051	−0.003^b	−0.009	−0.005	83	23
	(0.038)	(0.001)	(0.006)	(0.004)		
Advanced economies						
1975–2005	0.100^b	0.004^b	0.021^b	0.013^a	84	18
	(0.046)	(0.002)	(0.010)	(0.004)		
1975–1990	−0.026	0.002	−0.012	0.002	33	15
	(0.065)	(0.003)	(0.015)	(0.006)		
1990–2005	0.112^b	0.004^c	0.026^b	0.014^a	65	18
	(0.049)	(0.002)	(0.011)	(0.005)		
European countries						
1975–2005	0.080	0.003	0.017	0.014	66	15
	(0.060)	(0.004)	(0.014)	(0.007)		
1975–1990	−0.095	−0.007	−0.023	−0.017	24	12
	(0.082)	(0.006)	(0.018)	(0.013)		
1990–2005	0.099	0.004	0.025^c	0.016^b	53	15
	(0.063)	(0.003)	(0.015)	(0.008)		
Additional controls: $lny_{t-\tau}$, $Educ_{t-\tau}$, $(G/GDP)_{t-\tau}$, $Trade_{t-\tau}$, $Inflation_{t-\tau}$ and *time dummies*						

Note: Standard errors in parenthesis. Income inequality data are taken from the Luxemburg Income Study [37] dataset
[a]1% significance level
[b]5% significance level
[c]10% significance level

In Table 5, inequality indicators are entered one at a time (e.g., column (1) only includes the Gini coefficient, column (2) only includes the first quintile, and so on) and interaction terms for advanced and European economies are added in the set of controls. The upper part of Column (1) shows the results regarding the human capital Gini coefficient for the whole period, which can be interpreted as follows. When the dummy for the advanced countries is equal to zero, our results give a negative and statistically significant coefficient for the human capital Gini index similar to that found for the low and middle-income countries, −0.046 (see Table 1 column (2)).[24] When the dummy for the advanced countries is equal to one and that of Europe is equal to zero, the effect of human capital inequality on growth in the advanced countries that are not European is 0.046;[25] that is, more human

[24]Note that when the dummy for the high-income OECD countries is zero, the dummy for Europe is also zero. Therefore, the estimated coefficient of the inequality indicator corresponds to the low and middle-income countries as well as the high-income countries that do not belong to the OECD.

[25]When the dummy for the advanced countries is equal to one but that for the European countries is equal to zero, the effect of the human capital Gini coefficient for the non-European high-income OECD countries is 0.092–0.046.

Table 5 Dependent variable: per capita income growth rate

	Human capital inequality						*Income inequality (LIS)*			
	$Gini^h$	1^{st} $Quintile^h$	3^{rd} $Quintile^h$	5^{th} $Quintile^h$	1^{st} $Q^h/5^{th}$ Q^h	$Gini^h$	$Gini^y$	90/10	90/50	80/20
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Period 1965–2005						Period 1975–2005			
$Inequality_{t-\tau}$	−0.046[a]	−0.062	0.080[a]	−0.039[a]	−0.022	−0.047[a]	−0.039	−0.003[b]	−0.009	−0.005
	(0.014)	(0.057)	(0.018)	(0.013)	(0.018)	(0.014)	(0.035)	(0.001)	(0.006)	(0.004)
$Inequality_{t-\tau} * Advanced$	0.092[a]	0.030	0.007	0.064[a]	0.009	0.022	0.034	0.003[b]	0.003	0.004
	(0.031)	(0.076)	(0.020)	(0.024)	(0.023)	(0.056)	(0.023)	(0.001)	(0.004)	(0.003)
$Inequality_{t-\tau} * European$	−0.054	0.016	−0.014	−0.029	0.002	0.012	−0.019	−0.002	−0.003	−0.002
	(0.033)	(0.063)	(0.017)	(0.023)	(0.018)	(0.052)	(0.014)	(0.001)	(0.002)	(0.002)
Countries	102	102	102	102	102	101	23	23	23	23
Obs	744	744	744	744	744	736	104	104	104	104
	Period 1965–1985						Period 1975–1990			
$Inequality_{t-\tau}$	−0.085[a]	−0.080	0.131[a]	−0.055[a]	−0.029	−0.084[a]	−0.043	−0.005[c]	−0.017	−0.011
	(0.023)	(0.093)	(0.031)	(0.020)	(0.028)	(0.023)	(0.068)	(0.003)	(0.012)	(0.008)
$Inequality_{t-\tau} * Advanced$	0.082[b]	0.167	0.041	0.094[a]	0.051	0.125[c]	−0.007	0.001	−0.009	−0.002
	(0.037)	(0.106)	(0.032)	(0.034)	(0.032)	(0.074)	(0.061)	(0.004)	(0.010)	(0.007)
$Inequality_{t-\tau} * European$	0.025	0.012	0.004	−0.024	0.003	−0.010	−0.019	−0.003	−0.003	−0.004
	(0.045)	(0.085)	(0.029)	(0.035)	(0.025)	(0.073)	(0.023)	(0.002)	(0.003)	(0.003)
Countries	95	95	95	95	95	94	19	19	19	19
Obs.	393	393	393	393	393	389	39	39	39	39

	Period 1985–2005							Period 1990–2005		
$Inequality_{t-\tau}$	−0.035	−0.153	0.036	−0.029	−0.050	−0.037[c]	−0.066[c]	−0.004[a]	−0.012[c]	−0.006
	(0.022)	(0.106)	(0.029)	(0.021)	(0.031)	(0.022)	(0.038)	(0.001)	(0.006)	(0.004)
$Inequality_{t-\tau} * Advanced$	0.137[b]	−0.126	0.006	0.047	−0.023	−0.060	0.036	0.003[c]	0.004	0.004
	(0.064)	(0.140)	(0.033)	(0.041)	(0.039)	(0.106)	(0.025)	(0.002)	(0.004)	(0.003)
$Inequality_{t-\tau} * European$	−0.143[b]	0.074	−0.042	−0.037	0.012	0.039	−0.018	−0.001	−0.002	−0.002
	(0.063)	(0.101)	(0.028)	(0.036)	(0.029)	(0.101)	(0.016)	(0.001)	(0.002)	(0.002)
Countries	101	101	101	101	101	100	23	23	23	23
Obs.	445	445	445	445	445	440	83	83	83	83

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

Note: Standard errors in parenthesis. Income inequality data are taken from the Luxemburg Income Study [37]

[a]1% significance level

[b]5% significance level

[c]10% significance level

capital inequality is related to more growth in the group of countries that include Canada, United States, Japan, Korea, Australia, and New Zealand. On the contrary, the results suggest that human capital inequality has been detrimental to the growth rates of Continental Europe. When the European dummy is equal to one, the effect becomes negative (−0.08), although the impact is smaller in absolute value and not statistically significant at the standard levels.

Similar results are found with the quintiles. The results in columns (2–5) show that a higher share of education attained by the majority of the population as well as a lower concentration of education in the top quintile led to a more beneficial effect on the growth rates of the developing countries. In contrast, the greater concentration of education among the elite favored the per capita income growth rates in the non-European high-income OECD economies; when the dummy for the advanced countries is equal to one and that for Europe is equal to zero, the estimated effect of the 5^{th} quintile is 0.025. As with the Gini coefficient, the positive growth effect of a greater concentration of education in the top quintile becomes negative in the European region.

To find an explanation for the differential effect of human capital inequality on growth in both groups of countries we check whether the results are highly influenced by a specific country. Thus, we remove from the sample the non-European advanced economies one at a time. Results show that the positive effect of human capital inequality on the growth rates in the non-European high-income OECD economies is highly influenced by the characteristics of Korea, a country that has experienced both relatively high human capital inequality and high per capita income growth rates. The results for the Gini coefficient when Korea is removed from the sample are displayed in Column (6).

Finally, columns (7–10) give the results for the income Gini index and the income percentile ratios. The results show that income inequality has had a negative influence on the per capita income growth rates in the less developed countries; not only the estimated coefficients of the Gini index but also those of the percentile ratios are negative. The effects regarding the wealthy economies also show that the estimated coefficients of the income inequality indicators become positive for the advanced economies, mainly during the period 1990–2005, and negative for the European countries. Nevertheless, results concerning income inequality should be interpreted with caution since the data on income inequality are still scarce compared to those on human capital. In fact, most of the countries with data available on income inequality are wealthy economies. For example, the negative effect of income inequality on growth in low and middle-income countries and high-income countries not belonging to OECD is identified with five countries in the sample (Mexico, Hungary, Poland, Israel, and Taiwan). Thus, it is worth noting that the estimated coefficients of the interaction terms have to be interpreted with regard to these reduced number of countries in the reference category.

To summarize, whereas human capital inequality has no clear effect on the growth rates in the sample of advanced and European countries, a greater inequality in the distribution of income has encouraged the growth rates of these economies. However, using dummy variables for groups of wealthy economies, results point to a differential effect of inequality on growth even across rich countries. Although the results should be interpreted as tentative, given the influence of single-country characteristics, the relationship between human capital inequality and economic growth seems to be positive in Anglo-Saxon countries and negative in the European region.[26]

5 Conclusions

There is no consensus in the literature regarding the empirical effect of inequality on growth. To better understand this effect, this paper considers a larger data set and differentiates between income and asset inequality, the latter measured through human capital. Specifically, by estimating a dynamic panel data model that controls for country-specific characteristics, the paper analyzes the effect of income and human capital inequality in different regions of the world that include developing as well as rich economies.

Using data on human capital Gini coefficients, and the distribution of education by quintiles, our results show that higher human capital inequality has led to lower growth rates in most of the world's regions. In accordance with some theoretical models, the negative effect is found in less developed countries, where the relationship between human capital inequality and demographic variables is stronger. In the sample of higher-income countries, in contrast, no clear effect of human capital inequality on growth is found. However, a closer look shows that the lack of a clear effect in wealthy economies may be due to the fact that even in the rich countries, human capital inequality affects growth differently from one country to the next. In particular, using dummy variables for different groups of high-income countries, our findings suggest that whereas a greater inequality of human capital has reduced the growth rates in the European countries, it has had a positive influence in the Anglo-Saxon economies.

Likewise, the paper also finds evidence pointing to differing effects of income inequality on growth according to the level of development; a negative impact is found in the less-developed countries and a positive one in the higher-income economies. Moreover, the result is robust to the use of high-quality data from the Luxemburg Income Study [37] and to several measures of income inequality, including the Gini coefficient and ratios of income accruing to the top, middle, and lowest percentiles.

Overall, our results suggest that the effect of inequality on growth is complex, and that one should consider not only the source of inequality but also the stage of development of the region to be analyzed. A further investigation to better understand this relationship should analyze the mechanisms through which inequality influences investment and growth. The results found in this paper suggest that the mechanisms at work differ between rich and poor countries and even across wealthy economies.

[26]This result is in line with that of Brandolini and Rossi [17], who also find a positive association between income inequality and economic growth in the Anglo-Saxon countries and a negative relation in Continental Europe. Different institutions is the explanation put forward by the authors to account for the differential effect of income inequality on economic growth in the subgroups of rich countries.

Appendix

Table A1 Income Gini coefficients

Country	*UNU/WIDER-UNDP, World Income Inequality Database (WIID)*									*Luxemburg Income Study Database (LIS)*								
	1965	1970	1975	1980	1985	1990	1995	Mean	St.dv.	1970	1975	1980	1985	1990	1995	2000	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		–	0.303	0.308	0.305	0.336	0.346	0.320	0.020
Jordan	–	–	–	–	–	0.427	0.473	0.450	0.032	–	–	–	–	–	–	–	–	–
Turkey	–	0.560	0.510	–	–	0.441	0.415	0.481	0.066	–	–	–	–	–	–	–	–	–
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	–	–	–	0.445	0.466	0.495	0.491	0.474	0.023
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	–	0.422	0.390	0.397	0.383	0.394	0.017	–	–	–	–	–	–	–	–	–
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	–	–	0.267	0.269	0.271	0.277	0.296	0.276	0.012
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																		
Austria	–	–	–	–	–	–	–	–	–	–	–	–	–	0.227	0.277	0.257	0.254	0.025
Belgium	–	–	–	0.283	0.262	0.266	0.269	0.270	0.009	–	–	–	0.227	0.232	0.266	0.280	0.251	0.026
Denmark	–	–	–	0.310	0.310	0.332	0.332	0.321	0.013	–	–	–	0.254	0.236	0.218	0.225	0.233	0.016
Finland	–	0.318	0.270	0.309	0.308	0.262	0.261	0.288	0.026	–	–	–	0.209	0.210	0.217	0.247	0.221	0.018
France	0.470	0.440	0.430	0.349	0.349	–	–	0.408	0.055	–	–	0.293	0.288	0.287	0.288	0.278	0.287	0.005
Germany	0.281	0.336	0.306	0.321	0.322	0.260	0.274	0.300	0.029	0.271	0.264	0.244	0.268	0.257	0.273	0.275	0.265	0.011
Greece	–	–	–	–	0.399	0.418	–	0.409	0.013	–	–	–	–	–	0.349	0.333	0.341	0.011
Ireland	–	–	0.387	0.357	–	–	–	0.372	0.021	–	–	–	–	0.328	0.336	0.313	0.326	0.012
Italy	–	0.380	0.390	0.343	0.332	0.327	0.322	0.349	0.029	–	–	–	0.306	0.303	0.338	–	0.316	0.019
Netherlands	–	–	0.286	0.281	0.291	0.296	0.294	0.290	0.006	–	–	0.260	0.256	0.266	0.257	0.231	0.254	0.013
Norway	0.375	0.360	0.375	0.312	0.314	0.331	0.333	0.343	0.027	–	–	0.223	0.233	0.231	0.238	0.251	0.235	0.010
Portugal	–	–	0.406	0.368	–	0.368	0.356	0.374	0.022	–	–	–	–	–	–	–	–	–

Table A1 (continued)

Country	UNU/WIDER-UNDP, World Income Inequality Database (WIID)									Luxemburg Income Study Database (LIS)								
	1965	1970	1975	1980	1985	1990	1995	Mean	St.dv.	1970	1975	1980	1985	1990	1995	2000	Mean	St.dv.
Spain	–	–	0.371	0.334	0.318	0.325	0.350	0.340	0.021	–	–	0.318	–	0.303	0.353	0.336	0.326	0.022
Sweden	–	0.334	0.273	0.324	0.312	0.325	0.324	0.316	0.022	0.260	0.215	0.197	0.218	0.229	0.221	0.252	0.227	0.022
Switzerland	–	–	–	–	–	–	–	–	–	–	–	–	0.309	–	0.307	0.280	0.299	0.016
United Kingdom	0.243	0.251	0.233	0.249	0.271	0.323	0.324	0.271	0.038	0.267	0.268	0.270	0.303	0.336	0.344	0.343	0.304	0.036
Australia	–	–	–	0.393	0.376	0.412	0.444	0.407	0.028	–	–	0.281	0.292	0.304	0.308	0.317	0.300	0.014
Canada	0.316	0.323	0.316	0.310	0.328	0.276	0.277	0.307	0.022	0.316	0.289	0.284	0.283	0.281	0.284	0.313	0.293	0.015
Korea	0.343	0.333	0.360	0.386	0.345	0.336	0.382	0.355	0.022	–	–	–	–	–	–	–	–	–
Japan	0.348	0.355	0.344	0.334	0.359	0.350	–	0.348	0.009	–	–	–	–	–	–	–	–	–
New Zealand	–	–	0.300	0.348	0.358	0.402	–	0.352	0.042	–	–	–	–	–	–	–	–	–
United States	0.346	0.341	0.344	0.352	0.373	0.378	0.379	0.359	0.017	–	0.318	0.301	0.335	0.338	0.355	0.370	0.336	0.025
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	–	–	–	–	0.283	0.323	0.295	0.300	0.021
Poland	–	–	–	0.249	0.253	0.262	0.331	0.274	0.038	–	–	–	0.271	0.274	0.318	0.313	0.294	0.025
Mean	0.369	0.395	0.393	0.375	0.377	0.400	0.401	0.403	0.025	0.279	0.271	0.270	0.282	0.284	0.303	0.302	0.293	0.018
Std. dv.	0.079	0.097	0.093	0.085	0.083	0.095	0.097	0.088	0.015	0.025	0.038	0.035	0.054	0.056	0.061	0.058	0.054	0.007
Countries	17	26	36	40	40	52	45	56	56	4	5	12	18	21	23	22	23	23

Table A2 Country classification

Low and Middle income		High income			OECD
		NO OECD	OECD		
			European	No European	
Algeria	Honduras	Barbados	Austria	Canada	Canada
Benin	Jamaica	Trinidad and Tobago	Belgium	United States	Mexico
Bostwana	Mexico	Bahrain	Denmark	Japan	United States
Cameroon	Nicaragua	Hong Kong	Finland	Kore, Republic of	Japan
Central African Republic	Panama	Israel	France	Australia	Korea
Congo, Republic of	Argentina	Kuwait	Germany	New Zealand	Austria
Egypt	Bolivia	Singapore	Greece		Belgium
Gambia	Brazil	Taiwan	Iceland		Denmark
Ghana	Chile	Cyprus	Ireland		Finland
Kenya	Colombia		Italy		France
Lesotho	Ecuador		Netherlands		Germany
Liberia	Paraguay		Norway		Greece
Malawi	Peru		Portugal		Hungary
Mali	Uruguay		Spain		Iceland
Mauritania	Venezuela		Sweden		Ireland
Mauritus	Afghanistan		Switzerland		Italy
Mozambique	Bangladesh		United Kingdom		Netherlands
Niger	China				Norway
Rwanda	India				Poland
Senegal	Indonesia				Portugal
Sierra Leone	Iran				Spain
South Africa	Iraq				Sweden
Sudan	Jordan				Switzerland
Swaziland	Malaysia				Turkey
Togo	Nepal				Great Britain
Tunisia	Pakistan				Australia
Uganda	Philippines				New Zealand
Zaire	Sri Lanka				
Zambia	Syria				
Zimbabwe	Thailand				
Costa Rica	Hungary				
Dominican Republic	Poland				
El Salvador	Turkey				
Guatemala	Fiji				
Haiti	Papua New Guinea				
Total countries	70	9	17	6	27

Note: Classification according to income levels is taken from the World Bank in 2007

References

1. Aghion, Ph., E. Caroli, García-Peñalosa, C.: Inequality and economic growth: the perspective of the new growth theories. J. Econ. Lit. **37**, 1615–1660 (1999)
2. Alesina, A., Perotti, R.: Income distribution, political instability, and investment. Eur. Econ. Rev. **40**, 1203–1228 (1996)
3. Alesina, A., Rodrik, D.: Distributive politics and economic growth. Q. J. Econ. **109**, 465–490 (1994)
4. Alonso-Borrego, C., Arellano, M.: Symmetrically normalized instrumental-variable estimation using panel data. J. Bus. Econ. Stat. **17**, 36–49 (1999)
5. Arellano, M., Bond, S. R.: Some test of specification for panel data: Monte Carlo evidence and application to employment equations. Rev. Econ. Stud. **58**(2), 277–297 (1991)
6. Arellano, M., Bover, O.: Another look at the instrumental-variable estimation of error-components models. J. Econom. **68**, 29–52 (1995)
7. Atkinson, A.: Distribution and growth in Europe—the empirical picture: a long-run view of the distribution of income. In: Mimeo, 4^{th} ECFIN Annual Research Conference (2008)
8. Atkinson, A. B., Brandolini, A.: Promise and pitfall in the use of 'secondary' data sets: income inequality in OECD countries as a case study. J. Econ. Lit. **39**, 771–799 (2001)
9. Banerjee, A. V., Duflo, E.: Inequality and growth: what can the data say? J. Econ. Growth **8**, 267–299 (2003)
10. Barro, R. J.: Inequality and growth in a panel of countries. J. Econ. Growth **5**, 5–32 (2000)
11. Barro, R. J., Lee, J. W.: International data on educational attainment updates and implications. Oxf. Econ. Pap. **3**, 541–563 (2001)
12. Benabou, R.: Inequality and growth. NBER Working Paper No. 5658 (1996)
13. Bertola, G.: Factor shares and savings in endogenous growth. Am. Econ. Rev. **83**, 1184–1199 (1993)
14. Bertola, G.: Economic integration, growth, distribution: does the euro make a difference? this issue (2010)
15. Blundell, R., Bond, S.: Initial conditions and moment restrictions in dynamic panel data models. J. Econom. **87**, 115–143 (1998)
16. Bond, S., Hoeffler, A., Temple, J.: GMM estimation of empirical growth models. CEPR Discussions Paper No. 3048 (2001)
17. Brandolini, A., Rossi, N.: Income distribution and growth in industrial countries. In: Tanzi, V., Chu, K.Y. (eds.) Income Distribution and High-Quality Growth, pp. 69–105. MIT, Cambridge (1998)
18. Castelló-Climent, A.: Channels through which human capital inequality influences economic growth. Mimeo, IEI-University of Valencia (2010)
19. Castelló, A., Doménech, R.: Human capital inequality and economic growth: some new evidence. Econ. J. **112**(478), 187–200 (2002)
20. Castelló-Climent, A., Doménech, R.: Human capital inequality, life expectancy and economic growth. Econ. J. **118**, 653–677 (2008)
21. De la Croix, D., Doepke, M.: Inequality and growth: why differential fertility matters. Am. Econ. Rev. **93**(4), 1091–1113 (2003)
22. Deininger, K., Olinto, P.: Asset distribution, inequality, and growth. World Bank Policy Research Working Paper N° 2375 (2000)
23. Deininger, K., Squire, L.: A new data set measuring income inequality. World Bank Econ. Rev. **10**, 565–591 (1996)
24. Deininger, K., Squire, L.: New ways of looking at old issues: inequality and growth. J. Dev. Econ. **57**, 259–287 (1998)
25. Dollar, D., Kraay, A.: Growth is good for the poor. J. Econ. Growth **7**, 195–225 (2002)
26. Easterly, W., Sewadeh, M.: Global Development Growth Data Base. World Bank (2002)
27. Forbes, K.: A reassessment of the relationship between inequality and growth. Am. Econ. Rev. **90**(4), 869–887 (2000)
28. Galor, O., Tsiddon, D.: Technological progress, mobility, and economic growth. Am. Econ. Rev. **87**(3), 363–382 (1997)
29. Galor, O., Zeira, J.: Income distribution and macroeconomics. Rev. Econ. Stud. **60**, 35–52 (1993)
30. García-Peñalosa, C.: The economics of distribution and growth. Recent Issues and Experience, this issue (2010)
31. Griliches, Z., Hausman, J.: Errors in variables in panel data. J. Econom. **31**, 93–118 (1986)

32. Hansen, L. P.: Large sample properties of generalized method of moments estimators. Econometrica **50**, 1029–1054 (1982)
33. Hassler, J., Rodríguez-Mora, J. V.: Intelligence, social mobility, and growth. Am. Econ. Rev. **90**(4), 888–908 (2000)
34. Kaldor, N.: A model of economic growth. Econ. J. **67**, 591–624 (1957)
35. Knowles, S.: Inequality and economic growth: the empirical relationship reconsidered in the light of comparable data. J. Dev. Stud. **41**(1), 135–159 (2005)
36. Li, H., Zou, H.: Income inequality is not harmful for growth: theory and evidence. Rev. Dev. Econ. **2**(3), 318–334 (1998)
37. Luxemburg Income Study: Dataset available at http://www.lisproject.org (2007)
38. Moav, O.: Cheap children and the persistence of poverty. Econ. J. **115**, 88–110 (2005)
39. Mookherjee, D., Ray, D.: Persistent inequality. Rev. Econ. Stud. **70**, 369–393 (2003)
40. Panizza, U.: Income inequality and economic growth: evidence from American data. J. Econ. Growth **7**, 25–41 (2002)
41. Perotti, R.: Growth, income distribution and democracy: what data say. J. Econ. Growth **1**, 149–187 (1996)
42. Persson, T., Tabellini, G.: Is inequality harmful for growth? theory and evidence. Am. Econ. Rev. **84**, 600–621 (1994)
43. Saint-Paul, G., Verdier, T.: Education, democracy and growth. J. Dev. Econ. **42**, 399–407 (1993)
44. Sargan J.D.: The estimation of economic relationships using instrumental variables. Econometrica **26**, 393–415 (1958)
45. Székely, M., Hilgert, M.: What's behind the inequality we measure? An investigation using Latin American data. Research Department Working Paper N° 409, Inter-American Development Bank (1999)
46. UNU/WIDER-UNDP: World income inequality database, version 1.0, 12 September 2000. http://website1.wider.unu.edu/wiid/wiid.htm
47. Voitchovsky, S.: Does the profile of income inequality matter for economic growth?: Distinguishing between the effect of inequality in different parts of the income distribution. J. Econ. Growth **10**, 273–296 (2005)