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The Relationship between Inequality and GDP Growth: an Empirical Approach

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Abstract

The aim of this work is to analyze the relationship between inequality and economic growth. The results obtained by previous empirical papers were mixed. Authors such as Persson and Tabellini (1991) or Alesina and Rodrik (1994), in fact, find evidence of a negative relationship between the two variables of interest; on the contrary, Li and Zou (1998) and Forbes (2000) find that greater inequality is associated with faster economic growth. Barro (2000 and 2008) claims that inequality has a positive effect on GDP growth in advanced economies, but has a negative impact in developing ones.
The present work considers two samples of OCSE countries; in the full sample 33 countries are analyzed for the 1971-2010 period and inequality data are taken from the UNU-WIDER dataset. In the restricted sample 27 countries are considered for the 1981-2010 period and inequality data from the Luxembourg Income Study are used. The estimation technique employed are fixed effects, random effects and GMM Arellano-Bond. The Gini coefficient has been used as inequality measure and ten-years averages of the data have been computed in order to reduce the problem linked to the limited variability of the Gini coefficient across time.
In the case of the fixed effects and the GMM estimates on the full sample, positive and statistically significant estimated coefficients for the inequality measure are obtained. The value ranges from 1.2 to 1.5; this means that a 1% increase in inequality within a country would be followed by a more than proportional increase in the rate of economic growth in the following ten years. All the other estimated coefficients, when statistically significant, take the expected sign and the Sargan test confirms that the over-identifying restriction used for the GMM estimation are valid. However, there is room for further research, in particular by considering that: the relationship between the two variables of interest may be quadratic and not linear, the time horizon considered may significatively influence the estimation results and finally it would be necessary to extend the sample by also including developing countries (non-OCSE members).

Introduction

The aim of this work is to analyse the macroeconomic relationships between inequality, expressed by the Gini coefficient, and GDP growth. This issue has been studied in previous literature by following two main approaches: the first one refers to Kuznets, who in 1955 claimed that GDP trends has an impact on the level of inequality in a country. However, this relationship is not linear, but more complex (quadratic), assuming the form of an inverted "U". In the first stages, in fact, the process of economic development would make the concentration of resources rise, a phenomenon which is necessary in order to encourage investments. We would thus have an inverse relationship between development and inequality. Later in the process, however, thanks to factors such as the introduction of a progressive tax system, the level of inequality would fall and we would thus have a positive relationship between development and inequality.
The second approach to the problem encompasses the works of Barro (1996, 1999, 2000, 2008), Deininger and Squire (1996, 1997, 1998), Forbes (2000) and many others and aims at determining whether the pre-existing level of inequality within a country could hinder or prompt the process of growth and economic development. The present work follows this second approach; *per capita* GDP and *per capita* GDP growth will thus be considered as the dependent variables, whereas income inequality will be regarded as the independent variable. The OCSE countries will be considered for the 1960-2010 period, in order to take into account also the impact of the recent financial crisis which started in 2007.
The first section will present a review of the past literature on this theme, while the second section will be devoted to the formulation of the empirical model. The third part will present the estimates and the comments, the fourth one will include the robustness check and the fifth part will conclude.

1. The theoretical background

1.1 Inequality measures

The most used inequality measures are the Lorenz curve, the Gini coefficient and the dynamic measure of inequality; this last one considers the relationship between the father's income and the son's income, thus providing a measure of intergenerational mobility within a society. Deaton defines the Gini coefficient[1] as: "the average difference in income between all pairs of people divided by the average income" (Deaton 2013, p. 187). This coefficient is obtained by the Lorenz curve, which represents the cumulative percentage of income earned by each cumulative share of the population; population is represented in ascending order as regard to *per capita* income on the x-axis.

[1] Starting by data relative to the income of each quintile and supposing that within each quintile all individuals earn the same income, the Gini coefficient can be expressed as it follows:

$$GINI = 0.8 * (1 - 2Q_1 - 1.5Q_2 - Q_3 - 0.5Q_4)$$

where Q_i is the income share earned by the i-th quintile, group 1 is the poorest and group 5 is the richest (Barro, 1999, p. 18).

Graphically, the Gini coefficient is equal to the double of the area within the Lorenz curve and the 45° line and can range between 0 and 1, 0 representing a situation of perfect equality and 1 corresponding to the maximum possible level of inequality. This inequality measure presents some limits: it is a single number, an extremely synthetic inequality measure, which does not provide details on the actual income distribution within the economic system. Furthermore, several Lorenz curves may correspond to the same value of the Gini coefficient. However, Knowles claims that: "[t]he Gini coefficient is chosen as the measure of inequality, because the data are more readily available than for other possible measures and for comparability with the existing literature" (Knowles 2001, p. 12). Nevertheless, we have to keep in mind that it is a summary statistic, which does not say anything about the exact shape of the corresponding Lorenz curve. Arjon, Ladaique and Pearson (2003, p. 124) highlight that: "the Gini coefficient is particularly sensitive to changes in the middle of the income distribution" so it is an inadequate inequality measure in order to study the relationship between inequality and economic development. When the impact of income distribution on the investment decisions is analysed, the top quintile is the most relevant. On the other hand, if the effect of an unequal resource distribution on social instability and crime, the most relevant data are that of the bottom quintile, i.e. the 20% of the population earning the lowest incomes. Anand and Kanbur (1993, p. 30) refer that: "Ahluwalia uses as his (in-)equality index the income share of the lowest 40% of the population"; the two authors claim that it is a very particular inequality measure, as its value is entirely determined by a single point on the Lorenz curve. This is the reason why Deaton affirms: "I do not believe that there is any statement about income inequality that is true in every part of the world – except that it is difficult to measure" (Deaton 2013, p. 259).

Clarke (1992, p. 2) claims that a universally accepted inequality measure does not exist, so decides to employ in his paper the Gini coefficient, the Theil[2] index, the coefficient of variation of incomes and the share of income of the bottom 40% divided by the share of the top 20% of the population. This last measure has also been used by Persson and Tabellini (1991). Clarke seems to prefer the first three measures, among that quoted above: "[i]n general, the Gini coefficient, the coefficient of variation and Theil's index may be preferable to the ratio measure since they utilize more information" (Clarke 1992, p. 4). A variation in the income distribution within the broad group of the bottom 40%, the middle 40% and the top 20% of the population, in fact, would not influence the above-mentioned ratio, but would imply a change in all the other inequality measures. However:

"[a]lthough these measures give different values and even different orderings for countries in the sample, they are very highly correlated. […] In particular the coefficient of variation and Theil's index are extremely highly correlated" (Clarke 1992, p. 4). The author obtains a correlation between these two inequality measures equal to 0.99 and a correlation between the Gini coefficient and the Theil index equal to 0.97 (Clarke, 1992, p. 5). On this theme, also Barro (1999, p. 18) finds a high positive value of correlation (around 0.90, depending on the period considered) between the

[2] Contrary to the Gini coefficient, this index can be decomposed into variations between groups and within groups. Analytically, the Theil index can be expressed as it follows:

$$THEIL = -\sum \frac{1}{n} * \log(\frac{1}{n}) - (-\sum s_i * \log(s_i))$$

where s_i is the income share earned by the i-th individual on the total income (Clarke 1992, p. 4).

Gini coefficient and the income share earned by the top quintile. It can thus be claimed that the choice of the inequality measure, though being important, should not significatively influence the empirical results of the analysis. Perotti (1995, p. 8) uses the "combined share of the third and fourth quintile",

a measure that emphasizes the concept of middle class, whose dimension is often related to the level of equality; furthermore, it is a variable less subject to measurement errors.

As regards the problem of data comparability, Knowles (2001) claims that the previous empirical works used inequality data which were not consistently measured. He further affirms that inequality (expressed by the Gini coefficient) can be measured by using data on gross income, net income or expenditure; the unit of analysis, too, is not fixed and can be the individual or the household. Easterly (2006, p. 761) finds that inequality measured on the basis of expenditure data is generally lower than that measured on income data, as low income individual are usually able to increase their expenditure level thanks to government transfers. Obviously, net income inequality results lower than that computed on the basis of gross income, because the tax system is usually progressive. Knowles concludes that: "[m]aking cross-country comparisons of the distribution of income/expenditure which mix these different measures together is not likely to provide much useful information. However, this is precisely what is done in the existing literature" (Knowles 2001, p. 6). Deininger and Squire (1996, p. 581) claim that: "[m]ethodologically, the most justifiable way to ensure cross-country comparability of inequality measures is to use only measures that are defined consistently". For this reason, the dataset which the two authors define as "of high quality" is very small; we thus face a trade-off between coverage and comparability (Solt 2009, p. 5).

1.2 Available data

The Deininger and Squire dataset (1996) includes more than 2600 observations of the Gini coefficient and in many cases also relative to the shares of income earned by the population quintiles;

135 countries, both developed and developing, are included and data are referred to the 1947-1994 period, even if there is only a limited number of data until the '60s. This work has been enlarged in 1999 (and many times in the subsequent years), then becoming part of the World Income Inequality Database (WIID), realized by the World Institute for Development Economics Research (WIDER).

This makes now possible to employ cross-country techniques of analysis.

Deininger and Squire adopted three main data selection criteria (Atkinson 2000, p. 9): data must come from a national survey on family income or expenditure, this survey must be representative of the entire population and not only of the rural or of the urban one; finally, it must take into account all income sources, included in-kind payments. This is needed because the lowest-income groups usually depend more heavily on in-kind government benefits, so if these were excluded, inequality would be overestimated (Deininger and Olinto, 2000, p. 12). Furthermore, the authors tend to exclude data coming from tax records, as they consider them less representative. There are at least three problems concerning fiscal data: first of all, there is incomplete coverage, given that people earning an income which is below a certain threshold are not included. Secondly, the

definition of imposable income adopted by the fiscal authority may not coincide with the economist's concept of income. Finally, there can be difficulties in considering incomes related to fractions of years (Atkinson, 2000, p. 25). However, it should be taken into account that also household surveys present limits, for example in relation to the dimension and the structure of the sample, which has to be large enough in order to be considered representative.
The subset of data which the authors define as "high quality" includes around 700 observations relative to 115 countries (there is no more than one observation for each year in each country); all data with no clear reference to their primary source are excluded. However, also the Deininger and Squire dataset has some shortcomings; on this aspect Galbraith and Kum claim that: "[t]he D&S data set suffers from two defects. The first is unbalanced coverage, and the second is inaccuracy" (Galbraith and Kum 2000, p.2). The poorest countries and the first decades considered are largely under-represented. In addition, even in the high quality dataset, the Gini coefficient is not always computed on the basis of the same reference unit (income or expenditure, individual or household).
Perotti (1995, p. 9) emphasizes that: "data by economically active persons imply a greater inequality than data organized by households", as the share of economically active people in a family tends to diminish as the total household income increases. Data relative to economically active individuals do not include transfers, which are, at least in principle, included in data collected at household level, so the inequality level could be overestimated. However, these data do not include capital income such as interests, rents and dividends, which are usually more concentrated than labor income, so the inequality level could be under-estimated.
Deininger and Squire suggest two strategies to cope with the problem of data comparability. The first one consists in using only observations which are based on the same unit of analysis, but in this way the size of available data becomes very small. The second strategy is a standardizing procedure; given that the mean difference between the inequality measures (obtained by considering different reference units) is known, it would be sufficient to adjust data in order to properly take into account this difference (Solt 2009, p.4). The two authors find, for example, that the Gini coefficient measured on the basis of net income is usually smaller by 0.03 than that measured by referring to gross income. They thus suggest to add 0.03 to the observation based on net income, so that the latter would become "comparable with the gross-income-based observations" (Solt 2009, p. 4). Nevertheless, taxes are usually progressive (and not proportional, as this standardization method would imply), so a linear (constant) adjustment as that proposed above would be inadequate. Atkinson claims that: "simple «dummy variable» adjustment for differences in definitions are not a satisfactory approach to the heterogeneity of the available statistics" (Atkinson 2000, pp. 44-5), as methodological differences in data collection could influence not only the level, but also the inequality trend. Knowles (2001, p. 9) affirms that the only paper that used data measured in a consistent manner is that of Persson and Tabellini (1991), even though many of the observations used by the two authors are "of questionable accuracy".
Galbraith and Kum (2000, p. 4) question the three criteria chosen by Deininger and Squire for the data selection; including only data coming from household surveys leads to the exclusion of many countries, in which similar surveys have not been conducted. Analogously, the exigence that the sample is representative of the entire population implies the exclusion of those countries or periods in which only data about a part of the population are available. Such partial information,

however, could be relevant in order to analyse the evolution of inequality in the whole economic system under examination. Finally, Galbraith and Kum affirm that the inclusion of non-monetary benefits would not have a theoretical basis, since inequality is usually studied by considering monetary wages earned by different categories of workers and the structure of these compensations.

1.3 GDP growth and factors influencing it

GDP can be defined in three ways: it is the sum of all income earned in a year within a country, it is the sum of the added values produced in a year and it is the sum of the income spent during the period considered. GDP growth (g_t) is the variation, expressed in percentage terms, between two years:

$$g_t = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$$

From World War II until nowadays, most of the developed countries witnessed a positive GDP trend; according to Deaton: "[m]aterial living standards are improving in most countries of the world. Yet there is nothing logic that guarantees an automatic link between growth and reduction in global poverty" (Deaton 2013, p. 41). He then explains that the poorest countries could not experiment at all growth dynamics (as it happened for Africa in the '80s and '90s); furthermore, GDP growth could have benefited only the richest groups within each country.
Steady GDP growth is a relatively recent phenomenon, limited to certain countries, which are usually identified as "success economies": "[i]t is only in the last two hundred and fifty years that long-term and continuing economic growth in some parts of the world – but not in others – has led to persistent gaps between countries. Economic growth has been the engine of international income inequality" (Deaton, 2013, p. 4). The author emphasizes that this GDP evolution has been associated with rising inequality, starting from the Industrial Revolution, which he defines as "the Great Divergence" (Deaton 2013, p. 4), i.e. the moment in which income inequality started to become a more relevant phenomenon than in the past. The link between income, economic growth and inequality has been effectively summarized by Deaton as it follows: "[t]he evolution of income can be looked at from three different perspectives: growth, poverty and inequality. Growth is about average and how it changes, poverty about the bottom, and inequality about how widely incomes are spread across families or people" (Deaton 2013, p. 187).
In the present work GDP and GDP growth will be used as welfare indicators; however, they present non-negligible limits. According to Deaton: "[g]rowth of income is good because it expands the opportunities for people to live a good life", but: "there [is] really […] a problem with GDP as an indicator of wellbeing" (Deaton 2013, p. 174), as it does not include some activities which are not remunerated but have an important social role, as voluntary work or children education by parents. Furthermore, the positive relationship between *per capita* GDP and happiness seams to disappear beyond a certain income threshold, a phenomenon which is known as the Easterlin paradox (1974).

The variables usually employed to explain GDP evolution are the following (Barro, 2008, p. 6): health (life expectancy is often used as a proxy), education, openness to trade and investment, fertility rate and investment rate. It is also possible to add to the explanatory variables the initial GDP level; in this case the expected sign of the estimated coefficient is negative, following an idea of convergence, according to which countries starting from a lower GDP level tend to have larger GDP growth rates than the already developed ones.

1.4 Kuznets's hypothesis: GDP level affects inequality

There are two fundamental approaches to the problem; the first one is that of Kuznets, who links the evolution of the Gini coefficient to the average income level of an economy. He thus considers *per capita* GDP as the independent variable and inequality as the dependent variable. On the contrary, the second approach inverts the causality relationship between the two variables and tries to figure out whether high levels of inequality may hinder economic growth. In addition, Lundberg and Squire (2003) affirm that both inequality and growth may be simultaneously determined by other variables ("joint determinants", p. 341).
Kuznets claims that, in the first stages of the development process, when *per capita* income is still low, inequality is moderate, too. In the following phases, however, inequality must rise in order to make capital accumulation possible through savings. Kuznets refers to the Keynesians hypothesis of greater marginal propensity to save for those individuals who earn the highest incomes. The rise in inequality in this stage would be brought about by the workers' transition from the primary to the secondary sector. The author supposes that the agricultural sector, due to its inferior productivity, is characterized by a lower average income and a lower income dispersion (variability) than the manufacturing sector. Thus, the expansion of the manufacturing sector causes an increase in inequality within an economic system. In the following phases, once a certain income threshold has been met, inequalities begin to shrink due to a combination of several factors, such as legislation (e.g. the introduction of capital, inheritance or capital revenue taxes) or the dynamic characteristic of a growing economy, which favors the career of young entrepreneurs (Kuznets 1955, p. 9). Kuznets uses time-series data relative to United Kingdom, France and United States and theorizes a non-linear relationship between the inequality level and the *per capita* GDP level, in the form of an inverted "U". This is why some scholars believe that economic growth may help in reducing inequality in income distribution; for example, Dollar and Kraay title their paper: "Growth is Good for the Poor" (2002). It is important to notice that Kuznets assumes a quadratic-type relationship between inequality and growth, while most of the empirical work on this theme try to estimate a linear function.

1.5 The alternative hypothesis: inequality influences GDP growth

1.5.1 The fiscal policy mechanism

Aghion claims that: "[g]reater inequality in the distributions of income and land appears to slow down economic growth. Symmetrically, equality seems to be growth-enhancing" (1999, p. 8), he thus proposes a negative relationship between inequality and growth. The author further affirms that ex-post redistributive policies such as progressive taxation and subsidies, by contributing to the realization of a more equal income distribution, may favor economic growth: "redistribution can foster growth" (Aghion 1999, p. 5). The relevant concept here is that of ex-post inequality, i.e. inequality in the outcomes (expressed in terms of income ore wealth) and not that of ex-post inequality, which means inequality in the opportunities or in the starting points. In the present work, only redistributive policies aimed at reducing ex-post inequality will be considered.

Perotti (1995, p. 2) examines the main transmission mechanism that accounts for the sign of the relationship between redistribution and economic growth. These mechanisms are the following: the endogenously-determined fiscal policy, social and political unrest, constraint to indebtment due to imperfections in the capital market and the so called "endogenous fertility". The first issue is linked to the disincentive effect on the labor market linked to redistributive fiscal policies. More equal societies would witness, according to this theory, a weaker demand for such policies and thus the level of distortions and inefficiency in the economic decisions would be smaller. A greater level of investment would result from this and, as a consequence, also the growth rate would be higher. This theory is based upon two mechanisms; the first one is economic and linked to the impact of variations of the expected return on investment decisions ("[g]rowth increases as distortionary taxation decreases", Perotti 1995, p. 3), while the second is a political one: "[r]edistributive government expenditure and therefore distortionary taxation decrease as equality increases" (Perotti 1995, pp. 3-4). Furthermore, given that the individuals who earn a higher income have a greater marginal propensity to save than those who earn low incomes, the decision to take away resources from the rich in order to operate a redistribution in favor of the low income citizens would cause a decrease in the aggregate savings and in the aggregate investment as well, thus hindering economic growth (Knowles 2001). Gilles (1996, p. 721) underlines that redistributive fiscal policies are more distortionary when they are applied to the poorest and to the richest. The former, in fact, face a very high effective marginal tax rate, given that a small increase in their income may put them outside the system of subsidies (this is the so-called threshold effect); on the contrary, the latter according to the author would have more possibilities to evade their fiscal duties than the middle class. Perotti concludes that, as regards this first transmission mechanism, a positive relationship between equality and growth exists. However, empirical tests show that a high inequality level is usually associated to a lower (and not higher) level of taxation. Nonetheless, it is possible that inequality has a negative impact on the economic growth rate through the political channel even in absence of redistributive policies. The top income earners may decide to devote part of their resources to lobbying activities (which do not make GDP growth) by diverting them from otherwise productive investments, and thus reducing the aggregate economic performance of the system (Barro, 2000, p. 7). However, it should be taken into account that taxes are not necessarily distorsive; lump sum taxes do not affect the marginal return of capital, so investment decisions should not change (Perotti 1995, p. 24). On this theme, Fölster and Henrekson (2001, p. 15) claim that: "[e]mpirical studies of the relation between government size and economic growth have come to widely different conclusions", even if the authors themselves obtain evidence of a negative relationship between the size of Government public expenditure and economic growth in the rich economies. According to Aghion: "redistribution is found to have a positive rather than negative influence on growth" (Aghion 1999, p. 12). There would not be, thus the "big trade-off"

(Okun 1975), as Aghion claims: "there is not necessarily a trade-off between equity and efficiency" (Aghion 1999, p. 63). On this theme, Deininger and Olinto (2000, p. 6) find that the negative relationship between tax rate and economic growth ceases to exist if the fiscal revenue is used to invest in the production of public goods (e.g. infrastructures) or services (education) and not simply for government consumption. Gilles (1996) questions the hypothesis according to which the only determinant of investments is their after tax return; redistributive transfers could have the positive effect of discouraging the poor from engaging in criminal activities, thus contributing to the creation of a safer environment, which in turn could prompt investments. It is important to recall here the empirical results recently published by the International Monetary Fund (IMF Staff Discussion Note 2014), according to which the economic systems characterized by greater inequalities are those who implement the more relevant redistributive policies. However, this effects is particularly relevant in the OCSE countries, whereas it tends to become statistically insignificant otherwise. In addition, given a certain redistribution level, countries characterized by a lower inequality level are those who witness a greater rate of durable growth (i.e. medium and long term growth). In conclusion, redistributive policies are generally associated with a greater GDP growth rate and only in extreme cases this relationship changes its sign. These results imply that: "rather than a trade-off, the average result across the sample is a win-win situation, in which redistribution has an overall pro-growth effect, counting both potential negative direct effects and positive effects of the resulting lower inequality" (IMF Staff Discussion Note 2014, p. 17).

1.5.2 The role of the type of political regime

The above presented results obtained by Perotti in 1995 may depend on the type of political regime of the country in question. In democracies only, in fact, demands from the civil society for greater equality are met with the implementation of larger redistributive policies. This hypothesis is consistent with the results of Persson and Tabellini (1991), who operate a distinction between democracies and non-democracies in their paper. Knack and Keefer further investigate whether the negative effect of inequality on growth rate is a peculiarity of democracies only. On this theme the two authors quote the Meltzer-Richard theorem (1981), according to which, in countries characterized by smaller equality, the income tax rate chose by the median voter will be higher (Knack and Keefer 1997, p. 323). The two authors, however, claim that the result obtained by Persson and Tabellini (1991), i.e. that the negative relationship between inequality and growth does not exist in non-democratic regimes, is entirely due to measurement errors. Persson and Tabellini used in their paper some data that the authors themselves define as "of rather doubtful value". It is likely that the most inaccurate values are those relative to poor countries, which are often also ruled by a non-democratic government (Knack and Keefer, p. 327). Additionally, the classification of the kind of government made by the two authors can be questioned; for example El Salvador, South Korea, Madagascar, Mexico, Panama, Filippines and Senegal are included in the democracies, even if those countries did not presented in a continuative way over time all the essential characteristics of a purely democratic regime (Knack and Keefer 1997, p. 327). The authors thus refuse the hypothesis that the negative relationship between the two variables of interest only holds in democracies, by explaining that also who detains power in authoritarian regimes has to take into account the negative effects caused by inequality in terms of regime acceptancy by the population. In addition, inequality in absence of democracy may provoke an increase in the level of political violence and, at the extreme, a revolution; both events are usually regarded as damaging economic growth. Not by chance, the second transmission mechanism found by Perotti is that linked by political instability; he firstly states that investment and economic growth are decreasing in the level of socio-political instability and that instability is increasing in the level of inequality. As a consequence, more equity in resource distribution brings more growth (Perotti 1995, p. 4).

1.5.3 The role of capital market imperfection

Another possible transmission mechanism is linked to the existence of a capital market in which the perfect competition hypotheses are not respected. According to Aghion (1999, p. 13), inequality reduces the investment opportunities, because in order to obtain a loan it is necessary to have some capital to use as collateral. In addition an unequal resource distribution worsens the borrowers' incentives and creates macroeconomic volatility. The poor, in fact, given their lack of capital, may benefit from a relatively high marginal productivity of capital (we assume here the usual hypothesis of decreasing returns of the invested capital). However, they are not able to obtain loans from the banks in order to realize these high returns, because they have not enough capital to use as collateral. Redistributive intervention thus could make possible profitable investment and contribute to rise the economic growth rate. Aghion (1999, p. 19) further claims that redistributive policies improve, rather than worsen, incentives. He analyzes the case of the debtors of a bank: if they do not have their own capital invested in the project, as a consequence of the limited liability rule they will not incur in any loss in case of failure of their entrepreneurial idea (i.e. bankruptcy) and all costs will be borne by the bank. If the level of personal effort which is necessary to perform in order for the investment project to be successful is not observable, the individual will not have sufficient incentives to engage for the good outcome of the project. On the contrary, if the individual has some capital that can be used as collateral he will be encouraged to engage in the project, in order to avoid losing the invested resources. The theme of capital markets imperfections is also linked to the dynamics of human capital accumulation. It is usually assumed that economic growth is positively correlated with human capital accumulation within the economic system. Given a certain level of imperfection in the capital markets (e.g. it is not possible for poor people to get a loan in order to finance their education), this kind of investment tends to rise as equality increases; so a reduction in inequality would bring about greater economic growth. This last mechanism could also operate through the variable that Perotti defines as "endogenous fertility". The author finds that fertility diminishes and investment in human capital increases as inequality diminishes; the increase in *per capita* income is prompted by the decrease in fertility, so we get a further hint that a reduction in inequality may foster growth.

1.5.4 Other possible transmission mechanisms

Some studies explain the negative relationship between the two variables of interest by making reference to macroeconomic volatility (Aghion 1999, p. 9). This kind of volatility is positively correlated with the inequality level and negatively correlated with the rate of economic growth. A

more unequal society, as a consequence, would be characterized by greater instability in the macroeconomic variables (which would be due, in turn, to greater political instability) and would thus have a lower growth rate (Aghion 1999, p. 24). Galor and Tsiddon (1997, quoted in Forbes 2000, p. 870), on the contrary, try to explain the mechanisms through which inequality could positively affect the growth rate of an economy and the find the two most relevant ones. The first one is relative to the positive externalities created by human capital accumulation, a process which is initially made possible by resource concentration. In the initial phases of development, in fact, it is necessary that some individuals have a large resource availability, in order to be able to devote part of them to the education of their offspring, thus giving start to the human capital accumulation process. The second explanation is linked to technological innovation; the authors claim that the existence of high wage differential between different industries may encourage the most qualified workers to concentrate themselves in the sectors where the intensity of advanced technologies is the highest, thus contributing to the realization of higher rates of technological progress and, as a consequence, of economic growth.
In conclusion, from a theoretical viewpoint, it is possible to find arguments both in favor and against a positive relationship between inequality and growth rate of an economy. As it has been effectively summarized by Deaton: "[i]nequality can spur progress or it can inhibit progress" (Deaton 2013, p. 11). Easterly (2006, p. 756) operates a distinction between structural and market inequality, by claiming that the latter is the unavoidable consequence of our modern economic systems (free markets guarantee equality in the starting points, not in the outcomes) and has an ambiguous effect on the growth rate, because its elimination would have a negative effect on the individual's incentives. Structural inequality, on the other side, has according to Easterly an undoubtly negative impact on the growth rate. The considered time horizon, too, plays an important role; Knowles (2001) emphasizes that the empirical studies that found a positive relationship between inequality and GDP growth were focused on the short term, whereas if we extend the area of the research to the long term, the relationship between the two variables of interest becomes negative. Knowles concludes that inequality in gross income distribution is not significatively correlated with economic growth. However, this result could be substantially different if the dependent variable considered were net income or expenditure: "there is a negative correlation between inequality and growth across countries, but only when the focus is on inequality after redistribution has taken place. No evidence is found of a significant correlation between gross income and economic growth" (Knowles 2001, p. 28).

1.6 Literature review

1.6.1 Empirical evidence of a negative relationship between inequality and GDP growth

Perotti (1995, p. 23) obtains four general results from empirical analysis: (1) there is a positive relationship between equality and growth, (2) this relationship is less strong in poor countries, where it become statistically insignificant, (3) the distinction between democracies and non-democracies, despite being plausible, does not seem to be robust and (4) it does not seem possible to distinguish the effect of democracy from that of the pre-existing income level, given that most democracies are also countries characterized by high level of *per capita* income. Perotti concludes that societies characterized by a higher equality level witness an higher rate of human capital investment; however data do not seem to provide support for the hypothesis of distorsive effects caused by redistributive policies. Alesina and Rodrik (1994) analyze the 1960-1985 period and include in their sample many OCSE members and some developing countries, which are selected according to data availability. The inequality measure used in this context is the income Gini coefficient and, when available, the land Gini coefficient. The result is that: "income inequality is negatively correlated with subsequent growth" (Alesina and Rodrik 1994, p. 481).

The estimation results obtained by Clarke (1992, p. 15) show that, independently from the inequality measure used, "within the context of cross country growth regressions, initial inequality is negatively correlated with growth". These results are robust, i.e. they remain statistically significant also by adding additional explanatory variables to the econometric model employed. In contrast with the results of Persson and Tabellini (1991), the author finds that the relationship between inequality and growth does not substantially change in democracies and in non-democratic regimes. In addition, the relationship between the two variables of interest seems to be quantitatively non negligible: "[d]ecreasing inequality from one standard deviation above to one standard deviation below the mean increases the long term growth rate by approximately 1.3% per annum" (Clarke 1992, p. 23).
Persson and Tabellini (1991, p. 14) consider two different samples; the first one includes 9 countries (Austria, Denmark, Finland, Germany, the Netherlands, Norway, Sweden, United Kingdom and United States) for a period which ranges from 1830-50 to 1970-85. The second sample is larger (67 countries) and covers the 1960-85 period. The econometric estimation technique used is the that of the Ordinary Least Squares (OLS). In the first sample the estimated coefficient relative to the inequality measure chosen (the income share earned by the top 20% of the population) is negative and statistically significant: "an increase by 0.07 – one standard deviation in the sample – in the income share of the top 20% lowers the average annual growth rate just below half a percentage point" (Persson and Tabellini, 1991, p. 17). In order to avoid reverse causation problems (recall that, according to Kuznets' theory, it is the development level of an economy to determine the inequality level existing within it) the variable which expresses inequality (the top 20% income share) is measured at the beginning of each period. In the second sample, Persson and Tabellini decide to employ as inequality measure the ratio between the gross (before tax) income of the population top 20% and that of the bottom 40%, due to the larger data availability for this measure than for the income Gini coefficient. Also in this case, the relative estimate coefficient is negative and statistically significant at a 95% confidence level. If we consider only the non-democratic countries in the sample, however, the authors get an estimated value of the coefficient of interest which is no more statistically different from zero (Persson and Tabellini, 1991, p. 28). Assa (2012, p. 1) claims that: "the causality between inequality and growth runs in both directions"; the author considers 141 countries for the 1998-2008 period (the sample is then restricted to 100 countries due to insufficient data availability for the others) and uses the Gini coefficient as independent variable expressing the inequality level. The results seems to be consistent with those obtained by the previous literature (Persson and Tabellini 1991, Clarke 1992, Perotti 1995). Assa estimates a negative relationship between the initial income inequality level and subsequent GDP growth; the author, too, considers the Gini coefficient measured at the beginning

of the reference period or the previous years (1992-1998) in order to eliminate reverse causation problems in the estimation. As regards the estimation method, the author employs the Ordinary Least Squares (OLS) and the two-stages least squares (2SLS). Assa further verify the robustness of the obtained results by inserting in the model some instrumental variables. Assa (2012, p. 3) thus claim that: "[t]he coefficient for the GINI variable is negative and statistically significant at the 1%" in all the estimated model specifications. In addition: "[o]n average, a one standard-deviation increase in the GINI index results in 6%- 9% lower growth between 1998 and 2008". The negative effect of inequality on growth seems to be larger in the developing countries, while "there is no clear relationship between income inequality and subsequent growth in developed countries" (Assa, 2012, p. 4). The author concludes by claiming that: "beyond any moral objections to inequality, there are strong economic reasons to be concerned about it, as it retards growth under any political regime, at least in developing countries" (Assa 2012, p. 5). By using the method of the instrumental variables, Easterly, too, obtains a negative and statistically significant relationship between the Gini coefficient and *per capita* income: "[a] one standard deviation increase in the Gini (9 percentage points) reduces income by 1.1 standard deviations" (Easterly 2006, p. 767). Finally, Banerjee and Duflo (2003), reject the hypothesis of linearity of the model and show that the rate of economic growth is a quadratic function (which takes the form of an inverted "U") of net changes in the inequality measure. The two authors affirm that (p. 268): "data does not support the linear structure that has routinely been imposed on it". They thus conclude that: "[c]hanges in inequality, whatever their direction, are associated with lower growth in the next period" (Banerjee and Duflo, 2003, p. 287). Pagano, by applying the Generalized Method of Moments (GMM) developed by Arellano and Bond (1991), which the author defines as a technique "well suited to control for any measurement error and for any time-invariant omitted variables" (Pagano, 2004, p. 3), obtains empirical evidence of a negative relationship between the two variables of interest: "[q]uantitatively, the coefficient estimated […] are not small: one standard deviation increase in the Gini coefficient (equal to 7.4 percentage points in this sample […]) is associated with an increase in the long run of per capita income growth rate of 0.3 percentage point" (Pagano 2004, p. 9). Castelló-Climent (2007) considers the income as well as the human capital Gini coefficient as inequality measures and finds an inverted relationship between inequality and GDP growth. However, according to the author: "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 not so evident […] in the Advanced and European economies this coefficient is not statistically significant at the standard levels". (Castelló-Climent 2007, p. 9-10). The author thus concludes that: "[t]he 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" (Castelló-Climent 2007, p. 15); the impact of an unequal income and human capital distribution on economic growth would not be stable across time, nor in different regions.

1.6.2 Empirical evidence of a positive relationship between inequality and GDP growth

Partridge (1997) tries to solve the problem linked to heterogeneity in the definition and data collection methods in different countries by analyzing the relationship between inequality and economic growth within the united states, by using data collected with a relatively homogeneous methodology. The author obtains empirical evidence of a positive relationship between the Gini coefficient and the rate of economic growth. This result appears in contrast with the previous literature, and prompts Partridge to suppose that the model he proposes suffers from omitted-variable bias or that the relationship between inequality and growth changes substantially when it is analyzed at international or at intranational level.

Li and Zou (1998) use panel data techniques (random effects and fixed effects) and consider the 1960-1990 period. They obtain a positive estimated value of the coefficient relative to the inequality measure taken into account, i.e. the Gini coefficient. Furthermore, the sign of this coefficient, does not change in any of the four different model specifications proposed by the authors: "[f]or one-standard-deviation increase in the Gini coefficient, there will be an increase of 0.45-0.48% in the rate of economic growth" (Li and Zou, 1998, p. 325). These results are in striking contrast with those obtained by Alesina and Rodrik (1994) and those of Persson and Tabellini (1991). The theoretical reason of this empirical evidence may lay in the fact that entrepreneurs tend to save a greater share of their income than the other groups of the economy. So, in general, a higher level of income inequality could encourage greater savings of the rich people and, as a consequence, faster economic growth for the whole economy. Forbes (2000, p. 870) highlight two econometric problems that may arise in the estimation of the relationship between inequality and growth: the systematic measurement error on inequality data and biases due to the lack of some explanatory variables in the model (omitted-variable bias). On this theme Pagano (2004, p.2) claims that: "[s]ystematic measurement error could lead to either a positive or negative bias, depending on the correlation between the measurement error and the other variables in the regression". Forbes (2000) underlines that most of the empirical studies in this field have used the cross-country approach, without considering the dynamics linked to the long-term evolution of the variables of interest within each countries. However, according to Pagano: "[o]ne method of reducing omitted-variable bias is to use a panel technique which, by including fixed effect, at least gets rid of the biases caused by the omission of time-non-varying explanatory variables" (Pagano, 2004, p.2). The most suitable estimation techniques thus seems to be the panel data one; until 1996 this was not a feasible approach, due to data scarcity. However now, thanks to the work of Deininger and Squire, it has become doable. Forbes (2000, p. 872) estimates a model in which economic growth depends on the initial inequality level (represented by the Gini coefficient), on income, on human capital (i.e. the level of education) and on market distortion. This model is very similar to that used by Perotti (1995) and differs from that only for the introduction of country dummies and time dummies, which Forbes uses in order to take adequately into account the idiosyncratic non-observable factors of each country and the periods in which global shocks happened. For the variables representing stocks, the value measured at the beginning of each period is considered, in order to reduce endogeneity problems. The same model is estimated with different econometrics techniques, among which fixed effects, random effects and the Generalized Method of Moments developed by Arellano and Bond. Independently from the estimation method used, however, Forbes obtains positive and similar values of the estimated coefficient relative to the inequality measures in the various model specifications. She thus claims that: "[a] ten-point increase in a country's Gini coefficient is correlated with a 1.3 percent increase in average annual growth over the next five years" (Forbes 2000, p. 878).

However, given the subdivision of the period of interest in sub-periods of length equal to five years, this coefficient is likely to give account only of the short-term effects. By considering longer periods, i.e. ten-years periods, Forbes (2000, p. 878) find that the coefficient of interest, despite still being positive, reduces itself and becomes statistically insignificant. Beside the different time horizon considered, another reason which may explain the difference between the results obtained by Forbes and those of Perotti (1995), although the econometric models used by the two authors are very similar, lay in the fact that Perotti did not have the high quality data collected by Deininger and Squire in 1996 and thus used other, less precise, sources. In addition, the definition of inequality given by Perotti differs from that of Forbes. Perotti, in fact, uses as an explanatory variable the income share earned by the middle class and not the Gini coefficient. Forbes concludes that: "[c]ountries may face a trade-off between reducing inequality and improving growth performance" (2000, p. 885), but warns that we still do not have sufficient data to obtain policy indications. The sample of countries considered by Forbes is made up for above one half by OCSE members and African countries are largely under-represented. It is thus possible that the estimated relationship does not apply to very poor countries.

1.6.3 Empirical evidence of a non-statistically significant relationship between inequality and economic growth

Panizza (2002) proposes again the analysis of the relationship between inequality and growth within the United States, by using observations relative to the single states. The author, however, does not get statistically significant estimates for the coefficients relative to the inequality measures chosen (i.e. the Gini coefficient and the share of income earned by the third quintile). Given that these results are in contrast with those of Forbes (2000) and Partridge (1997), the author concludes that: "the cross-state relationship between inequality and growth is not robust to small changes in the data or econometric specification" (Panizza 2002, p. 37). Barro (1999, p. 32), with a panel data approach finds: "[a] little overall relation between income inequality and rates of growth and investment. For growth, there is an indication that inequality retards growth in poor countries but encourages growth in richer places". He identifies the turning point in which this relationship changes its sign in an income level equal to 2070 $ (expressed in 1985 dollars). A possible explanation of this result consists in the fact that the constraints to investment due to the restrictions in the credit market may have greater consequences in the poor countries. From data relative to the whole group of countries included in the sample, however, it emerges that: "differences in Gini coefficients for income inequality have no significant relation with subsequent economic growth. One possible interpretation is that the various theoretical effects of inequality on growth […] are nearly fully offsetting" (Barro 2000, p. 17). Furthermore, the author obtains from the estimations results a statistically insignificant relationship between the Gini coefficient and the investment rate, in contradiction with the traditional explanation according to which inequality is linked to the rate of economic growth through the channel of investment in physical and human capital. In another paper, Barro (2008) argues that the total effect of income distribution inequality on economic growth is weak and often not statistically significant. However, he gets from the data the indication that inequality may have positive effects on growth in rich countries and negative effects in the poor ones. The estimated coefficient relative to the inequality measure (i.e. the Gini coefficient) is equal to -0.036 (Barro, 2008, p. 6). An increase in inequality of one standard deviation would cause a reduction in the growth rate equal to around 0.4% per annum. In this case the author identifies the turning point in correspondence of a *per capita* income equal to 11'900 $ per year. Starting from that threshold, inequality would have a positive impact on the growth rate. In reality, the countries considered in the sample are divided into two subsets, the first one composed of rich countries and the second of poor ones, Barro (2008) finds weak empirical evidence of a positive relationship between the two variables of interest in the first group of countries. Similar results are obtained by Grijalva in 2011, by applying the Generalized Method of Moments. The author considers several time horizons and concludes that: "the nature of the relationship between inequality and growth changes over time" (Grijalva 2011, p. 26). In the short and medium term (5-10 years), Grijalva finds evidence of an inverted "U" (i.e. not linear) relationship between inequality and growth. However this relationship seems to disappear in the long term (20 years). In the last considered time horizon, the author finds confirmation of the results obtained by Barro (2000): "I find evidence consistent with Barro (2000) that inequality is bad for growth in poor countries but good for growth in rich ones. But while Barro finds this association for 10-years periods, I find it for 20-year periods" (Grijalva 2011, p.22). Deininger and Squire (1998) focus not only on inequality in the income distribution, but also on inequality in wealth distribution. The two authors use data on land distribution as a proxy in order to analyze the impact of an unequal asset distribution on economic growth. On this theme Perotti affirms that: "[e]mpirically […] this is unlikely to be a serious problem because the shapes of the two distributions [of income and of wealth] generally vary together in cross-sections, although the former tends to be more skewed than the latter" (Perotti 1995, p. 8). From the estimation results of Deininger and Squire it emerges that a (positive) difference equal to one standard deviation (around 9 percentage points) in the initial value of the income Gini coefficient should be associated to a (negative) difference in growth rates equal to 0.4 percentage points. (Deininger and Squire, 1998, p. 269). In addition, if regional dummies are introduced in order to take into account the specific characteristics of each continent, the estimated coefficient relative to the inequality measure becomes statistically insignificant. The analysis which considers the initial concentration of the distribution of land obtains similar results. On this aspect Deininger and Squire note that, within the group of non-OCSE countries included in the sample, 15 present a value of the land Gini coefficient which is superior to 0.7; among these 15 countries only 3 experimented a growth rate greater than 2.5% in the analyzed period (1960-1992) (Deininger e Squire, 1998, p. 271). The authors thus claim that: "[u]nequal distribution of assets, more than of income, can be an impediment to rapid growth" (Deininger and Squire 1997, p.39). However, "inequality is not a significant determinant of future growth in democratic countries" (Deininger and Squire 1998, p.260); in particular, the two authors point out that: "the relationship between initial asset inequality and future growth disappears in high-income economies" (Deininger and Squire 1998, p. 260). In conclusion, it exists a negative relationship between the initial inequality level in the wealth distribution and the subsequent growth rate of an economy, but this relationship can explain only a limited fraction of the existing differentials recorded in the growth rates at international level and tends to disappear in the advanced economies.

1.6.4 Methodological considerations

It has been proposed that the relevant differences in the empirical results obtained by the empirical studies arise due to the different econometric techniques employed for the estimation: "[w]hile most cross-country studies find a negative relationship between inequality and economic growth, studies that use panel data suggest the presence of a positive relationship between inequality and growth" (Panizza 2002, p.1). On this theme Halter (2010, p. 1) notes that: "[e]stimators based on time-series (differences-based) variation indicate a strong positive link while estimators (also) exploiting the cross-sectional (level-based) variation suggest a negative relationship", he links these differences to the different impact of inequality on economic growth in the short-middle and in the long run. Voitchovski agrees, by affirming "[m]ethods that rely on the time-series variation in the data tend to indicate a positive effect of inequality on growth (e.g. Li and Zou, 1998; Forbes, 2000) while methods that rely on the cross-sectional information tend to indicate a negative effect (e.g. Persson and Tabellini, 1991)" (Voitchovski 2005, p. 290). Castello-Climent (2007, p. 5) underlines the inadequacy of cross-section estimation methods: "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". It is thus correct to use data with a panel structure (i.e. data relative to different countries across a certain time span), which allows to take into account the non-observable heterogeneity of each country. Arjona, Ladaique and Pearson (2003, p. 124) argue that the inverse relationship between inequality and GDP level may suffer of a reverse causality problem; the authors explain that the advanced economies are usually characterized by a lower inequality level than the developing ones, but the causality relationship between the two variables of interest is not clear. A possible explanation of the correlation between equality and growth may lay in the fact that only rich countries may afford a greater redistribution level and thus greater equality (Easterly 2006, p. 757). By means of a cross-section estimate it would be possible to obtain as a result that more inequality is associated to a lower level of economic growth (we talk about advanced economies) or development (when we talk about developing countries), although it is the development level to determine the inequality level and not *vice versa*. Furthermore, the three authors recall that the value and sign of the estimated coefficients obtained with econometric techniques are always referred to marginal variations. So if, for example, we get a positive relationship between the level of redistribution and the rate of growth, this does not mean that any increase in the size of redistributive policies will lead to a positive impact on economic development. It is highly likely, in fact, that a threshold exists, beyond which further redistributive measures are damaging for economic growth, due to their distorsive effects.

Figure 1: Summary table of literature review

Author	Country and period	Inequality measure	Results
Persson and Tabellini 1991	9 developed countries (1830-1985); 67 developed and developing countries (1960-85).	In the first sample: income share of the top quintile. In the second sample: ratio between the income share of the bottom 40% and that of the top 20%.	Negative relationship, which becomes statistically insignificant in non-democratic countries.
Clarke 1992	Around 70 countries, 1970-88.	Gini coefficient, Theil index, income coefficient of variation and ratio between the income share of the bottom 40% and that of the top 20%.	Negative relationship
Alesina and Rodrik 1994	70 (46 in the restricted sample) OCSE countries and developing countries, 1960-85.	Income and land Gini coefficient.	Negative relationship
Perotti 1995	67 countries, data closest as possible to year 1960.	Income share of the third and of the fourth population quintile.	Negative relationship (not statistically significant in poor countries).
Partridge 1997	USA (48 single states), 1960-90.	Gini coefficient and income share of the third quintile.	Positive relationship
Deininger and Squire 1998	87 countries, among which 27 developing countries, 1960-92.	Income and land Gini coefficient.	Negative relationship, which become statistically insignificant with the inclusion of regional dummies.
Li and Zou 1998	46 countries, 1960-90.	Income Gini coefficient	Positive relationship
Forbes 2000	45-67 countries, for the most part OCSE members; 1970-95.	Income Gini coefficient	Positive relationship
Knowles 2001	Around 40 countries 1960-90.	Income Gini coefficient	Negative relationship
Panizza 2002	USA (48 single states), 1940-80.	Gini coefficient and income share of the third quintile.	Not statistically significant results.
Banerje and Duflo 2003	45 countries, 1965-90.	Income Gini coefficient	Changes in inequality in whatever direction are associated to negative changes in the growth rate.
Pagano 2004	40 countries, 1950-1990	Income Gini coefficient	Positive relationship in rich countries, negative relationship in the poor ones.
Easterly 2006	More than 100 countries, 1960-98.	Ratio between the extension of land suitable to grow wheat and that suitable for sugarcane.	Negative relationship
Castelló-Climent 2007	56 countries, 1965-2000	Income and human capital Gini coefficient	Negative relationship
Barro 2008	47-70 countries, 1965-2003/4	Income Gini coefficient	Positive relationship in rich countries, negative relationship in the poor ones.
Grijalva 2011	Around 100 countries, 1950-2007	Income Gini coefficient	Inverted "U" relationship the short and medium term (5-10 years). In the long term the results confirm Barro (2008).
Assa 2012	141 countries (100 in the restricted sample), 1998-2008.	Income Gini coefficient	Negative relationship in the developing countries, less evident in the advanced economies.

Source: author's own elaboration

2. Definition of the empirical model

2.1 Sample description

In the present work the Gini coefficient has been chosen as inequality measure, in order to have maximum comparability with the existing literature. For the estimate in the full sample (33 OCSE countries), data from the updated Deininger and Squire dataset have been used (source: UNU WIDER 2014). Where several observation for the same country in the same years were available, those classified by the authors as the most accurate ones have been used[3]. Where several observation of the same quality where available for the same country in the same year, the arithmetic mean of the available observation has been computed and used for the estimates.
In the restricted sample (27 countries), instead, inequality data from the Luxembourg Income Study (LIS) have been considered. LIS data are widely recognized as of higher quality; however, country and period coverage is smaller. Observations in the LIS are available for a relatively large number of country only from 1981, while the Deininger and Squire dataset (corrected and updated in 1999, 2005, 2008 and finally in 2014) contains several data on the '50s and the '60s.
The full sample includes 33 OCSE countries; Iceland has been excluded due to lack of data on income inequality; these data, in fact, are only available for the 2004-2011 period. Data relative to all the other explanatory variables have been taken from the World Development Indicators database (WDI, 2014) of the World Bank (updated at 01.07.2014). The relevant period for this work goes from 1961 to 2010 in the full sample and from 1981 to 2010 in the restricted sample.

2.2 The empirical model

The model to estimate has been elaborated on the basis of the existing literature, which has been analysed in the first section of this work. Even though the aim of this paper consists in analysing the relationship between inequality and economic growth, other explanatory variables, on the basis of Barro (1999, 2008), Forbes (2000), Alesina e Rodrik (1994), have been added to the model, in order to avoid omitted variable bias.
The equation to be estimated is the following:

$$Y_t = \alpha_0 + \alpha_1 \ln(GDP_{t-1}) + \alpha_2 GINI_{t-1} + \alpha_3 FDI_t + \alpha_4 School_t + \alpha_5 Open_t + \alpha_6 Life_t + \alpha_7 Ocse_t + \alpha_8 d_{1,t} + \alpha_9 d_{2,t} + \alpha_{10} d_{3,t} + \varepsilon_t \text{ (I)}$$

For simplicity's sake, the equation relative to a single country is presented here. However, this work utilizes panel data (i.e. it considers several countries in a time period), so in the following paragraph the panel notation will be introduced.

Y_t stands for the annual *per capita* GDP growth rate, computed according to the following equation:

[3] All observation are classified with a number, which ranges from 1 to 4, where 1 stands for maximum accuracy and 4 means less accuracy or no clear reference to the primary source (Solt 2009). Only observations classified with the numbers from 1 to 3 has been employed in the present work.

$$Y_t = \ln\left(\frac{GDP_t}{GDP_{t-1}}\right) = \ln(GDP_t) - \ln(GDP_{t-1})$$

On this theme, Forbes (2000, p. 879) affirms: "[t]his paper and virtually all other work on growth utilize the logarithm of initial income, whereas Perotti simply uses initial income"; this factor can thus play an important role in explaining the different results obtained by the two authors.
The model can be rewritten as it follows:

$$\ln(GDP_t) = \alpha_0 + \gamma_1 \ln(GDP_{t-1}) + \alpha_2 GINI_{t-1} + \alpha_3 FDI_t + \alpha_4 School_t + \alpha_5 Open_t + \alpha_6 Life_t + \alpha_7 Ocse_t + \alpha_8 d_{1,t} + \alpha_9 d_{2,t} + \alpha_{10} d_{3,t} + \varepsilon_t \quad \text{(II)}$$

Where $\gamma_1 = \alpha_1 + 1$. The source for the *per capita* GDP data is the World Bank (*per capita* GDP measured in current US$ has been considered here). The $\ln(GDP_{t-1})$ variable has been included in order to take adequately into account the theory of convergence, which has been summarized in section 1. The expected sign of the estimated coefficient α_1 is thus negative; However, if the model is estimated in specification (II), we would get $\gamma_1 < 1$, as a consequence of the transformation.
$GINI_{t-1}$ is the value of the Gini coefficient in the period before the one considered. The lagged value is used instead of the current value, $GINI_t$, in order to avoid endogeneity bias. The aim of this work is to analyse the impact of inequality on economic growth; however, as explained in the first section, the economic theory claims the existence of a causal relationship which runs in the opposite direction, i.e. GDP level influences the inequality level of an economic system. The two variables of interest are thus linked by the Kuznets curve, which can be represented by the following equation:

$$GINI_t = \beta_0 + \beta_1 GDP_t - \beta_2 GDP_t^2$$

As a consequence, the Gini coefficient measured at time t is correlated to the GDP level in the same year, GDP_t. By following the specification (II) of the model, it is immediate to see that $GINI_t$ is also correlated with the error term, ε_t. The hypothesis of non-correlation between regressors (explanatory variables) and errors is thus not respected. This econometric problem can be solved in two ways: the first one consist in the use of instrumental variables which must be correlated to the explanatory variable we are interested in, $GINI_t$, but are not correlated with the error term. Easterly (2006) identifies a possible instrumental variable in the availability of land (exogenous) suitable for wheat, in relation to that available for sugarcane cultivation. The author explains the relationship with this instrumental variable (which he defines: "lwheatsugar") and the level of inequality in a society: "[s]ugarcane is a labor-intensive crop requiring cheap labor to be economical. The sugarcane stalks are also very bulky to transport long distances and must be ground within days of the harvest. This led to economies of scale and led the typical sugar holding historically to be a plantation that was large enough to produce enough sugarcane to cover the fixed costs of a sugar mill right on the plantation" (Easterly 2006, p. 757, footnote 2). However, it is plausible that this variable is particularly relevant in the study of the dynamics of the developing countries, but has less explanatory power in the case of developed countries. For this reason, and for the difficulty in finding other valid instrumental variables, it has been preferred here to use the lagged value of the Gini coefficient, $GINI_{t-1}$, which is correlated with ε_{t-1} but not with ε_t, under the hypothesis of error independence.

- FDI_t measures the net influx of Foreign Direct Investments in a country in a given year, this is expressed as a percentage of the country's GDP. Given that, in most cases, FDI are greater where the restriction to the capital movements are limited and economic freedom is guaranteed, this variable has been used has a proxy for the rule of law, i.e. the institutional stability and the degree of protection of the property rights. The expected sign of the coefficient is thus positive. The data source is the World Bank.
- $School_t$ stands for the level of education of the population. In the past, contrasting effects of male and female education on economic growth of a country have been found by empirical studies[4] (these effects are often strongly dependent on the type of familiar relationships, on cultural factors and on the time horizon considered). As a consequence, in the present work it has been decided to consider the aggregate data, without operating a gender distinction. The indicator used here is the gross secondary school enrollment ratio of the World Bank, which records: "the total enrollment in secondary education, regardless of age, expressed as a percentage of the population of official secondary education age" (WB). This variable can take values greater than 100%, due to factors such as: "the inclusion of over-aged and under-aged students because of early or late school entrance and grade repetition" (World Bank[5]). The expected sign of the estimated coefficient of $School_t$ is positive (Barro 2003).
- $Open_t$ measures the economic openness; it has been computed by dividing the sum of import and export of good and services of a country by its GDP. Data have been provided by the World Bank. The expected impact on the dependent variable is positive (Pagano 2004, p. 11). According to Barro (2008, p. 8), in fact: "[g]rowth is particularly encouraged by greater international openness, higher life expectancy, better rule of law, and lower fertility".
- $Life_t$ represents life expectancy at birth (expressed in years), as recorded by the World Bank. As for the education variable, also in this case for the sake of simplicity a gender distinction has not been operated. The expected sign of the coefficient is positive (Barro 2008).
- $Ocse_t$ is a dummy variable which takes value 1 if the country in year t was an OCSE member and 0 otherwise. In this work only countries which were OCSE members at 31.12.2010 has been included; however different countries accessed to OCSE in different periods (see Appendix 1). The invitation or admission of a country to OCSE is an *a posteriori* process, based on the achieved economic success of a certain country. It is thus possible to object that some countries which were not able to converge to the GDP level of the advanced economies, perhaps due to an extremely high inequality level, have been excluded from the sample and our estimation results are biased as a consequence. The $Ocse_t$ variable has been introduced precisely in order to eliminate selection bias problems. This dummy allows us to distinguish

[4] According to Grijalva (2011, p. 28): "[t]he most puzzling result concerns human capital. The effect of female education does not seem to contribute to growth at any time frame. […] Male education on the other hand has a positive coefficient attached to it in most specifications, but it only becomes significant in the very long-run".
[5] Source: http://data.worldbank.org/indicator/SE.SEC.ENRR (18/07/2014).

between the years in which a country was outside OCSE and that in which, on the contrary, the country was an OCSE member. This variable can be interpreted in two ways: firstly, it is possible to claim that OCSE membership produces positive effects on the economic growth of a country. Secondly, $Ocse_t$ can be regarded as function of the GDP level attained in the previous years:

$$Ocse_t = f(GDP_{t-1}, GDP_{t-2}, GDP_{t-3}, GDP_{t-4}, \dots)$$

So this variable could be used as a proxy for the lagged values of GDP of order superior than one, which have not been included in the model. In both cases, the expected sign for the estimated coefficient is positive.

- $d_{1,t}, d_{2,t}$ e $d_{3,t}$ are dummies which take values 1 if the observation in question is referred, respectively, to the '70s, to the '80s or to the '90s and take value zero otherwise ($d_{4,t}$ dummy refers to the 2000s and is the omitted attribute). This qualitative variable has been included in order to take into account the positive trend experienced by *per capita* GDP in advanced economies starting from the '50s. In the restricted sample only the dummy $d_{3,t}$ is used.
- ε_t is the error term. It is assumed here that the errors are independent and identically distributed (i.i.d.).

2.3 The estimation method

In the present work a panel data approach is employed; each observation has two pedices, i (which identifies the country) and t, which stands for the time period (decade) to which each observation belongs ("[p]anel data are repeated observations on the same cross-section", Colin Cameron and Trivedi 2005, p. 697). In the full sample we have: $i = 1, 2 \dots, 33$ and $t = 1, 2, 3, 4$, while in the restricted sample $i = 1, 2 \dots, 27$ and $t = 1, 2$. Only for some countries, however, there are available observations for the entire time period considered: the panel is unbalanced. Panel data estimation methods allow to take into account the individual effects, i.e. non-observable idiosyncratic characteristics of each specific country, which could influence the dependent variable. The simultaneous exploiting of time-series and cross-sectional information allows us to avoid biases due to individual non-observable heterogeneity and to operate a distinction between common parameters and specific effects relative to the single country or period. According to Colin Cameron and Trivedi (2005 p. 695): "[c]ross-sections models have certain inherent limitations […] they do not shed light on intertemporal dependence of events". Two possible approaches are possible: fixed effects and random effects. In the first one the individual effects are treated as parameters to be estimated, while in the second one they are included in the error term. The fixed effect method does not require to make any hypothesis on the individual effects. In order to be able to apply the random effects method, on the contrary, it is necessary that these individual effects, being included in the error term, are independent from the explanatory variables. For completeness in the present work both of these approaches are employed, but we should keep in mind that: "[t]he main caveat using random effects is that it is consistent only if the individual specific effect is uncorrelated with the other covariates [explanatory variables]. However, […] we think that there are structural factors specific to each country that may affect the relationship between inequality and growth, i.e. that may be correlated with the other explanatory variables" (Grijalva 2011, p.14-15).

As regards the fixed effects method, it cannot be applied in presence of time-invariant explanatory variables (i.e. variables which do not vary over time, but vary only across countries). In our model, the Gini coefficient tend to remain constant or to change slightly from one year to another in the same country and to witness major changes only in the long run. To solve this problem, all the explanatory variables have been expressed in ten-years averages, thus dividing the period of interest in four sub-periods: 1971-1980, 1981-1990, 1991-2000 and 2001-2010. For the two lagged variables, i.e. Gini coefficient and *per capita* GDP, the reference period goes from 1961 to 2000. The use of ten-years averages has another advantage, since it gives less relevance to extreme values due to the short-term fluctuations of the economic cycle. The result is: "a panel that is more balanced and less subject to business-cycle fluctuations" (Pagano 2004, p. 3). As a consequence, the $Ocse_t$ dummy takes value 1 if, in the ten-years period considered, the country was an OCSE member for at least five years.

Observations with missing value for one or more of the variables have been eliminated; this seems not to be a problem form the econometric viewpoint, since these observations are missing at random and not selected in a systematic way. From our sample it emerges that countries with higher levels of *per capita* income are not necessarily those with the more accurate data. For example, in our sample there is only one observation (relative to the 2001-2010 period) for Luxembourg, while in the case of Turkey, there are data available for the full period (1971-2010). In this way we obtained the full sample, which contains 106 observations relative to 33 OCSE countries (period 1971-2010, on the basis of UNU-WIDER and WB data) and the restricted sample, which consists in 46 observations relative to 27 countries[6] for the period 1981-2010 (on the basis of LIS and WB data).

For both random effects and fixed effects estimates, we hypnotizes that the errors $\varepsilon_{i,t}$ relative to different countries and periods are independent and identically distributed (i.i.d.) and that the explanatory variables are independent from the error terms. In both cases the estimated model is that in specification (I), since in this case the estimated coefficient relative to the variable $\ln(GDP_{i,t-1})$ can be immediately interpreted. By using the fixed effect approach, the model presented above is reformulated as it follows:

$$Y_{i,t} = \alpha_{0,i} + \alpha_1 \ln(GDP_{i,t-1}) + \alpha_2 GINI_{i,t-1} + \alpha_3 FDI_{i,t} + \alpha_4 School_{i,t} + \alpha_5 Open_{i,t} + \alpha_6 Life_{i,t} + \alpha_7 Ocse_{i,t} + \alpha_8 d_{1,i,t} + \alpha_9 d_{2,i,t} + \alpha_{10} d_{3,i,t} + \varepsilon_{i,t}$$

In order to solve the problem linked to the possible presence of individual effects which are time-invariant, the model is rewritten in time differences (i.e. difference from the time mean), so that the individual effects cancel out.

$$\Delta Y_{i,t} = \alpha_1 \Delta \ln(GDP_{i,t-1}) + \alpha_2 \Delta GINI_{i,t-1} + \alpha_3 \Delta FDI_{i,t} + \alpha_4 \Delta School_{i,t} + \alpha_5 \Delta Open_{i,t} + \alpha_6 \Delta Life_{i,t} + \alpha_7 \Delta Ocse_{i,t} + \alpha_8 \Delta d_{1,i,t} + \alpha_9 \Delta d_{2,i,t} + \alpha_{10} \Delta d_{3,i,t} + \Delta\varepsilon_{i,t}$$

[6] The LIS dataset includes 28 OCSE countries; however, Japan has been excluded from the sample, due to lack of data relative to the period of interest.

where: $\Delta Y_{i,t} = Y_{i,t} - \bar{Y}_{i\cdot}$ e $\Delta GINI_{i,t-1} = GINI_{i,t} - \overline{GINI}_{i\cdot}$, and the same holds for all the other variables; $\bar{Y}_{i\cdot}$ represents the mean of the dependent variable computed for each individual on the time period considered. This is the model reformulated according to the random effects approach:

$$Y_{i,t} = \alpha_0 + \alpha_1 \ln(GDP_{i,t-1}) + \alpha_2 GINI_{i,t-1} + \alpha_3 FDI_{i,t} + \alpha_4 School_{i,t} + \alpha_5 Open_{i,t} + \alpha_6 Life_{i,t} + \alpha_7 Ocse_{i,t} + \alpha_8 d_{1,i,t} + \alpha_9 d_{2,i,t} + \alpha_{10} d_{3,i,t} + \varepsilon_{i,t}$$

The structure of the error terms is the following: $\varepsilon_{i,t} = u_i + v_{i,t}$, where u_i represents the error component specific of each individual (in this context, of each country). We assume that the u_i are all independent and identically distributed between countries, that the $v_{i,t}$ terms are i.i.d. between countries and time periods, that the two components of the error term are independent and that the explanatory variables are independent from the errors.

However, the model we want to estimate is a dynamic one, as it includes among the explanatory variables the natural logarithm of the *per capita* GDP in period $t-1$. The estimation with panel data technique, both random effects and fixed effects, if applied to a dynamic model, gives a biased estimate (there is the so called Nickell bias), due to the correlation between explanatory variables and error terms, which violates the initial assumptions. Grijalva (2011, p. 15) claims that: "both fixed effects and random effects are inconsistent in the presence of a lagged dependent variable".

Both $\ln(GDP_{i,t})$ and $\ln(GDP_{i,t-1})$, in fact, are function of the same individual effect (*country effect*, u_i). As a consequence: "the standard fixed-effect estimator is biased and inconsistent" (Pagano 2004, p. 4). This bias is eliminated by using the generalized method of moments (GMM) in the version proposed by Arellano and Bond in 1991, by choosing as instrumental variables the lagged values of the endogenous variable of order greater than one ($\ln(GDP_{i,t-2})$, $\ln(GDP_{i,t-3})$ and so on) and the first differences of the exogenous explanatory variables (for example $\Delta FDI_{i,t} = FDI_{i,t} - FDI_{i,t-1}$). The problem we want to solve lies in the fact that the endogenous lagged variable, $\ln(GDP_{i,t-1})$ contains the error term $\varepsilon_{i,t-1} = u_i + v_{i,t-1}$ and is thus correlated with it; given that the error at time t is defined as: $\varepsilon_{i,t} = u_i + v_{i,t}$, $\ln(GDP_{i,t-1})$ is correlated with $\varepsilon_{i,t}$, because both contains u_i. The hypothesis of non-correlation between explanatory variables and error terms is thus violated. As a consequence, in order to obtain an unbiased estimate of the coefficient in the present work the GMM Arellano-Bond method will also be employed. This technique consists in rewriting the model in first differences, so that the error component which is idiosyncratic to each country (which is the source of the correlation between lagged endogenous variable and errors) cancels out.

Following Forbes (2000, p. 873) the model is here considered in specification (II):

$$\Delta \ln(GDP_{i,t}) = \gamma_1 \Delta \ln(GDP_{i,t-1}) + \alpha_2 \Delta GINI_{i,t-1} + \alpha_3 \Delta FDI_{i,t} + \alpha_4 \Delta School_{i,t} + \alpha_5 \Delta Open_{i,t} + \alpha_6 \Delta Life_{i,t} + \alpha_8 \Delta Ocse_{i,t} + \alpha_8 \Delta d_{1,i,t} + \alpha_9 \Delta d_{2,i,t} + \alpha_{10} \Delta d_{3,i,t} + \Delta \varepsilon_{i,t}$$

Where: $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$, and the same holds for all the other variables; the error term is now equal to:

$$\Delta \varepsilon_{i,t} = u_i + v_{i,t} - u_i - v_{i,t-1} = v_{i,t} - v_{i,t-1}$$

However, we recall that: $\Delta \ln(GDP_{i,t-1}) = \ln(GDP_{i,t-1}) - \ln(GDP_{i,t-2}) = Y_{i,t-1}$, this variable contains (within the error term $\varepsilon_{i,t-1}$) the element $v_{i,t-1}$ and thus has a non-zero correlation with $\Delta\varepsilon_{i,t}$. It becomes necessary to introduce one or more instrumental variables for $\Delta \ln(GDP_{i,t-1})$ and for this we employ, as explained, before, the lagged values of the endogenous variable of order superior or equal to two.

The element $\ln(GDP_{i,t-2})$ is correlated with the error $\varepsilon_{i,t-2} = u_i + v_{i,t-2}$, but, under the hypothesis of i.i.d. $v_{i,t}$, $\ln(GDP_{i,t-2})$ has zero correlation with $\Delta\varepsilon_{i,t} = v_{i,t} - v_{i,t-1}$. In order for this estimation method to be applicable, it is necessary that the error terms $v_{i,t}$ are not correlated between them. Given that the GMM estimator is based on the first differences, to perform this estimate we eliminate from the sample the countries for which there are not available at least two consecutive observations (Grijalva 2011, p. 13). In the full sample this means the exclusion of Belgium, Estonia and Luxembourg, and the total number of observations drops from 106 to 103. In the present work the GMM method has been applied only to the full sample, due to the larger amount of available data. In the restricted sample, in fact, the maximum available number of periods is $T = 2$ and for eight countries there is only one observation (Belgium, Estonia, Greece, Hungary, Luxembourg, Slovak Republic, Czech Republic), so the number of instrumental variable that could be used is really limited (the only lagged value of the endogenous variable that could be used is $\ln(GDP_{i,t-2})$). It is thus unlikely that the estimated coefficients would be statistically significant at the usual confidence levels.

3. Results of the estimates

In the following paragraphs the results of the estimates performed on the full sample as well as on the restricted ones with different estimation methods are reported. The software used for the estimation is STATA 13.

Figure 2: Random effects, full sample (1961-2010)

```
Random-effects GLS regression                   Number of obs      =       106
Group variable: country                         Number of groups   =        33

R-sq:  within  = 0.7689                         Obs per group: min =         1
       between = 0.4200                                        avg =       3.2
       overall = 0.6506                                        max =         4

                                                Wald chi2(10)      =    232.69
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

diff_ln	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lngdpt1	-.3511043	.0456056	-7.70	0.000	-.4404896	-.261719
gini	.2834559	.3558065	0.80	0.426	-.413912	.9808237
fdigdp	.0059526	.010635	0.56	0.576	-.0148915	.0267968
school	.0042794	.0019918	2.15	0.032	.0003757	.0081832
openness	.0013785	.0010459	1.32	0.187	-.0006714	.0034284
lifeexp	.034471	.011013	3.13	0.002	.012886	.056056
ocsedummy	.1429557	.0667899	2.14	0.032	.0120499	.2738615
d1	.2071191	.097506	2.12	0.034	.0160108	.3982275
d2	.0192055	.0680357	0.28	0.778	-.114142	.1525529
d3	-.0087442	.0517995	-0.17	0.866	-.1102695	.092781
_cons	.4061691	.6542248	0.62	0.535	-.876088	1.688426

Source: author's own elaboration

The above output gives information on the explanatory power (goodness of fit, R^2, called R-sq in the table), i.e. in which percentage of the variance of the dependent variable can be explained by means of the independent (explanatory) variables included in the model. Among the three R^2 values reported in figure 2, R-sq overall is identical to the value of R^2 in the model with sample pooling, i.e. the model which would be obtained by assuming the absence of differences across individuals (OLS estimation method). R-sq between, instead, is obtained by expressing the regression in terms of time-averaged observation (for each observation the averages on the cross-sectional units have been computed). Lastly, R-sq within is referred to the cross-sectional average observations, which are obtained by computing, for each unit, the time averages[7]. We assume that the correlation between regressors and individual effects u_i is zero, because otherwise the estimation with the random effects method would be unconsistent. The Wald test[8], reported in figure 2, states as null hypothesis (H_0) that all the model coefficients (excluded the constant term) are zero, while the alternative hypothesis (H_A) claims that the coefficients are different from zero.

[7] Source: Manera and Galeotti 2005, *Applicazione 1*, p. 19, available upon registration at: www.carocci.it
[8] Source: http://www.stata.com/manuals13/xtxtabond.pdf (p. 7, 08/08/2014)

Given that the p-value (prob > chi2) is equal to zero, we can reject the null hypothesis at a confidence level equal to 99%. The model chosen seems thus to adequately represent the reality. This result is also confirmed in the case of the random effects estimate on the restricted sample.

Figure 3: Random effects, restricted sample (1981-2010)

```
Random-effects GLS regression                   Number of obs      =        46
Group variable: country                         Number of groups   =        27

R-sq:  within  = 0.2357                         Obs per group: min =         1
       between = 0.8011                                        avg =       1.7
       overall = 0.6368                                        max =         2

                                                Wald chi2(8)       =     64.87
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

diff_ln	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lngdpt1	-.1753432	.0553935	-3.17	0.002	-.2839124	-.066774
gini	.1073413	.5600986	0.19	0.848	-.9904317	1.205114
fdigdp	-.0071108	.011662	-0.61	0.542	-.0299679	.0157464
school	.0012846	.0018706	0.69	0.492	-.0023817	.0049509
openness	.0023366	.001203	1.94	0.052	-.0000213	.0046944
lifeexp	-.0108691	.0180577	-0.60	0.547	-.0462617	.0245234
ocsedummy	-.0010239	.0744551	-0.01	0.989	-.1469533	.1449055
d3	-.0156011	.0522074	-0.30	0.765	-.1179258	.0867236
_cons	2.777808	1.071464	2.59	0.010	.6777762	4.87784

Source: author's own elaboration

The presence of the constant term in the regression output obtained with the fixed effects method is due to a peculiarity of STATA[9], whose reference model is expressed by the following equation:

$$y_{i,t} = \alpha + \sum_{r=2}^{K} \beta_r x_{r,i,t} + u_i + v_{i,t}$$

When the fixed effect estimation method is chosen, STATA considers the constant term α as part of the individual effects, which are not given by the u_i alone, but by the $\alpha_i = \alpha + u_i$.

Figure 4: Fixed effects, full sample (1961-2010)

[9] Source: Manera and Galeotti 2005, *Applicazione 1*, p. 15.

```
Fixed-effects (within) regression               Number of obs      =       106
Group variable: country                         Number of groups   =        33

R-sq:  within  = 0.8371                         Obs per group: min =         1
       between = 0.2328                                        avg =       3.2
       overall = 0.3377                                        max =         4

                                                F(10,63)           =     32.38
corr(u_i, Xb)  = -0.7844                        Prob > F           =    0.0000
```

diff_ln	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lngdpt1	-.6340793	.0732482	-8.66	0.000	-.7804542	-.4877044
gini	1.224641	.4579736	2.67	0.010	.3094543	2.139829
fdigdp	.0280364	.0138377	2.03	0.047	.0003839	.055689
school	.0043504	.0026545	1.64	0.106	-.0009542	.0096549
openness	-.0022193	.0024231	-0.92	0.363	-.0070615	.0026228
lifeexp	.0174403	.0147238	1.18	0.241	-.0119828	.0468634
ocsedummy	.1528837	.0973145	1.57	0.121	-.0415838	.3473512
d1	-.6932489	.2239044	-3.10	0.003	-1.140686	-.2458116
d2	-.455012	.1341305	-3.39	0.001	-.7230505	-.1869735
d3	-.2412314	.0744019	-3.24	0.002	-.3899117	-.0925511
_cons	4.327049	1.276318	3.39	0.001	1.776531	6.877567

Source: author's own elaboration

With the fixed effects estimation, contrary to the random effects case, the absence of correlation between the individual effects and the regressors is not a necessary condition to get a consistent estimate. The estimated value of that correlation is reported in figure 4 and in both samples (full and restricted) differs from zero. Corr(u_i, Xb) is computed as the correlation between the fitted values of the regression:

$$\sum_{r=2}^{K} \hat{\beta}_r \hat{x}_{r,i,t} = y_{i,t} - \hat{\alpha} - \hat{u}_i - \hat{v}_{i,t}$$

and the estimated values of the u_i, the variable part of the individual effects[10]. The F-test, which is used to study the joint significance of all the regressors (excluded the constant) allows us to claim that, in the full samples, the coefficients are different from zero at a confidence level of 99%. In the restricted sample, however, the model seems not to be correctly formulated, since the p-value of the F-test is greater 30%, i.e. well above the usual threshold of 5%. The result of this last estimate is thus uniquely reported in Appendix 4 for brevity. In order to determine whether the most appropriate estimation method is random effects or fixed effects, the Hausman test has been performed on the estimation results relative to the full sample. The result of this test, reported in figure 5, shows that the random effects approach seems to be preferable here.

[10] Source: Manera and Galeotti 2005, *Applicazione 1*, pp. 18-19.

Figure 5: Hausman test on the full sample

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lngdpt1	-.6340793	-.3511043	-.282975	.0573187
gini	1.224641	.2834559	.9411856	.2883428
fdigdp	.0280364	.0059526	.0220838	.0088533
school	.0043504	.0042794	.0000709	.0017547
openness	-.0022193	.0013785	-.0035979	.0021857
lifeexp	.0174403	.034471	-.0170307	.0097726
ocsedummy	.1528837	.1429557	.009928	.0707759
d1	-.6932489	.2071191	-.900368	.2015583
d2	-.455012	.0192055	-.4742175	.1155948
d3	-.2412314	-.0087442	-.2324871	.0534083

```
                 b = consistent under Ho and Ha; obtained from xtreg
  B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

          chi2(10) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                   =        6.94
        Prob>chi2 =      0.7307
```

Source: author's own elaboration

According to Manara and Galeotti[11], by performing this test we compare an estimator which is consistent under the null hypothesis of absence of correlation between the regressors and the individual effects (u_i) and under the alternative hypothesis of presence of this correlation (the fixed effects estimator), with another estimator, which is efficient under the null, but inconsistend under the alternative (the random effects estimator). In our case, the p-value of the test is very high (around 73%), well above the usual threshold of 5% (corresponding to a 95% confidence level); so we do not have enough empirical evidence to reject the null hypothesis. This means that both estimation methods are consistent and that the random effects one is efficient. This test has not been performed on the restricted sample, given that in this case the result of the fixed effect estimation were not statistically significant. However, the result of the Hausman test has to be interpreted with caution; in the context of a dynamic model such as the one we are interested in both random effects and fixed effects method are biased and inconsistent, as explained before.

[11] Manara and Galeotti 2005, *Applicazione 1*, p. 30.

Figure 6: GMM (Arellano-Bond), full sample (1961-2010)

```
Arellano-Bond dynamic panel-data estimation  Number of obs         =        73
Group variable: country                      Number of groups      =        30
Time variable: period
                                             Obs per group:    min =         1
                                                               avg =  2.433333
                                                               max =         3

Number of instruments =     13               Wald chi2(7)          =   3585.92
                                             Prob > chi2           =    0.0000
Two-step results
                                (Std. Err. adjusted for clustering on country)
```

lngdpt	Coef.	WC-Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lngdpt						
L1.	.6636221	.0586698	11.31	0.000	.5486314	.7786129
gini	1.49799	.4519993	3.31	0.001	.6120876	2.383893
fdigdp	.0450332	.0124411	3.62	0.000	.0206491	.0694174
school	-.0001574	.0030569	-0.05	0.959	-.0061488	.005834
openness	-.0040247	.0024038	-1.67	0.094	-.008736	.0006866
lifeexp	.0247664	.0182232	1.36	0.174	-.0109505	.0604833
ocsedummy	.1433906	.1342508	1.07	0.285	-.1197361	.4065174
_cons	1.323117	.855778	1.55	0.122	-.3541769	3.000411

```
Instruments for differenced equation
        GMM-type: L(2/.).lngdpt
        Standard: D.gini D.fdigdp D.school D.openness D.lifeexp D.ocsedummy
Instruments for level equation
        Standard: _cons
```

Source: author's own elaboration

In this case, too, the Wald test seems to confirm the validity of the model formulation. The constant term represents here the trend of GDP growth across time (it has a similar role to that of the time dummies in the fixed effects and random effects estimates) and not surprisingly has a positive estimated value.

The two-steps version of the GMM Arellano-Bond has been employed here; this means that in the first stage the parameter θ, upon which the matrix V of variances-covariances of the error terms depends, is estimated. Secondly, by using the obtained value $\hat{\theta}$ in the estimated matrix $\hat{V}$, we proceed to estimation of the coefficients, according to the following formula:

$$\hat{\gamma}_{GMM} = (\Delta W' Z \hat{V}^{-1} Z' \Delta W)^{-1} * \Delta W' Z \hat{V}^{-1} Z' \Delta y$$

where W is the matrix of the explanatory variables, Z contains the instrumental variables and Δy represents the dependent variable expressed in first differences.

Figure 7: Sargan test on the full sample

```
Sargan test of overidentifying restrictions
        H0: overidentifying restrictions are valid

        chi2(5)      =  5.833804
        Prob > chi2  =    0.3227
```

Source: author's own elaboration

In figure 7 the result of the Sargan test of over-identifying restrictions has been reported[12]; this test has been performed in order to verify the adequacy of the instrumental variables chosen. The p-value here is well above the usual 5% threshold (it is equal to 32.27%), so it is not possible on that basis to reject the null hypothesis. It seems thus that the instruments are valid and the model formulation is correct. However, it should be considered that, according to the literature on the theme, the Arellano-Bond estimator is particularly suitable when the sample is characterized by a limited number of periods and a large number of individuals (this is the: "small T, large N assumption", Grijalva 2011, p. 9). In our sample N is equal to 33 countries at most, which is a quite small size. As a consequence, the obtained results could be biased due to the small sample size.

Independently from the estimation method employed, a more unequal income distribution seems to have a rather positive impact on *per capita* income in the next period. These results could confirm Barro's hypothesis (2000 and 2008), according to which inequality damages economic growth in poor countries, but on the contrary encourages growth in high income economies. All the countries considered in the present work are currently OCSE members and thus characterized by middle-high levels of *per capita* income. However, the results obtained in the empirical analysis should be interpreted with caution, as the estimated coefficient relative to the variable $GINI_{i,t-1}$ is statistically significant only in the fixed effects and GMM Arellano-Bond estimates performed on the full sample. In the restricted sample, in fact, most of the estimated coefficients are not statistically significant at the usual confidence level (95%). It is likely that this is due to the limited number of countries included in the sample and to the restricted time period considered. Also the random effects estimate performed on the full sample has given results which are not statistically significant for the variable of interest, $GINI_{i,t-1}$. On the contrary, in the fixed effects and GMM Arellano-Bond estimates on the full sample, the estimated coefficient for the variable $GINI_{i,t-1}$ is positive and statistically significant at a 99% confidence level. This result is consistent with those of Barro (2008), Forbes (2000) and Pagano (2004). In order to verify if the economic mechanisms which link inequality and economic growth are different in the developed and in the developing economies, it would be interesting to add to the model an interaction term between the Gini coefficient and a variable which expresses the level of development of a country. However, to successfully accomplish this, also countries with a low level of development should be included in

[12] In this case the number of these restrictions is equal to five, which is the difference between the number of instruments (13) and the number of explanatory variables, included the constant and the lagged value of the endogenous variable (8).

the sample. In general, the estimated coefficients related to the other explanatory variables have in most of the cases the expected sign and in some cases they are statistically significant.
For example, life expectancy has a positive impact on *per capita* income in all the specification of the model, as well as the dummy which expresses OCSE membership. In addition, the estimated coefficient for the variable $\ln(GDP_{i,t-1})$ is negative in all the estimates performed with the random effects and standard effects methods, thus giving support to the theory of economic convergence. Also the GMM estimation result is consistent with this theory, but in this case the coefficient interpretation is not immediate. As explained in the prevous section, in order to employ the GMM Arellano-Bond estimation method, the model specification (II) was used, so in the regression output we get $\gamma_1 = 0.664$. However, the coefficient of interest in order to verify whether there is economic convergence or not is equal to $\alpha_1 = \gamma_1 - 1 = 0.664 - 1 = -0.336$, so also in this case the estimated value is negative. As regards the openness of an economy (variable $Open_{i,t}$), it is not straightforward to determine the impact of this factor on GDP growth, since statistically significant estimates of the relative coefficient of both positive and negative sign have been obtained. However, the impact of this variable seems to be quantitatively small.
Furthermore, according to our expectations, the estimated coefficients related to the variables representing secondary education, life expectancy at birth, foreign direct investment and OCSE membership, when statistically significant, always have a positive sign, thus confirming the idea that
an increase in these variable is associated with faster GDP growth. Lastly, the estimated coefficients for the time dummies are in most cases statistically significant at a 95% or at a 99% confidence level. In the case of the fixed effects estimate on the full samples, in particular, all the three dummies are statistically significant at a 99% confidence level and the relative estimated coefficients present increasing values ($\hat{\alpha}_8 < \hat{\alpha}_9 < \hat{\alpha}_{10}$), thus giving indication of a positive impact of the passing of time on economic growth.

4. Robustness check

In order to verify if the obtained results are sensitive to slight changes in model formulation, another estimation has been performed on the full sample, by including some additional explanatory variables: fertility rate ($Fertility_{i,t}$, expresses as the number of childbirths for woman), public expenditure ($G_{i,t}$, general government final consumption expenditure, expressed as a percentage of GDP) and tertiary school enrollment rate ($TertiaryEdu_{i,t}$). For the first two additional variables the expected sign of the estimated coefficient is negative (Pagano 2004, p. 11 and Barro 2008, p. 6), while for the third one is positive. Data relative to these three variables have been taken from the World Develpment Indicators (01.07.2014) of the World Bank.

Figure 8: Robustness check, fixed effects

```
Fixed-effects (within) regression               Number of obs      =       100
Group variable: country                         Number of groups   =        29

R-sq:  within  = 0.8659                         Obs per group: min =         2
       between = 0.1273                                        avg =       3.4
       overall = 0.2914                                        max =         4

                                                F(13,58)           =     28.81
corr(u_i, Xb)  = -0.8262                        Prob > F           =    0.0000
```

diff_ln	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lngdpt1	-.715197	.0765653	-9.34	0.000	-.868459	-.561935
gini	.9327248	.4628453	2.02	0.049	.0062393	1.85921
fdigdp	.034108	.0144075	2.37	0.021	.0052683	.0629477
school	.0015859	.0028112	0.56	0.575	-.0040413	.0072132
openness	-.0035603	.0026559	-1.34	0.185	-.0088766	.001756
lifeexp	-.0051267	.0204783	-0.25	0.803	-.0461185	.0358651
ocsedummy	.1081736	.0992106	1.09	0.280	-.0904179	.3067651
fertility	-.1422955	.0857537	-1.66	0.102	-.3139503	.0293593
g	-.0051888	.0088081	-0.59	0.558	-.0228201	.0124425
tertiaryedu	.0087678	.0024431	3.59	0.001	.0038774	.0136583
d1	-.6720281	.2411072	-2.79	0.007	-1.154657	-.1893995
d2	-.398599	.1566131	-2.55	0.014	-.7120941	-.0851039
d3	-.2015458	.0887701	-2.27	0.027	-.3792386	-.0238531
_cons	7.164492	2.047169	3.50	0.001	3.066639	11.26235

Source: author's own elaboration

Figure 9: Robustness check, GMM Arellano-Bond

```
Arellano-Bond dynamic panel-data estimation  Number of obs         =        71
Group variable: country                      Number of groups      =        29
Time variable: period
                                             Obs per group:    min =         1
                                                               avg =  2.448276
                                                               max =         3

Number of instruments =     16               Wald chi2(10)         =   4185.15
                                             Prob > chi2           =    0.0000
Two-step results
                                (Std. Err. adjusted for clustering on country)
```

lngdpt	Coef.	WC-Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lngdpt						
L1.	.5747756	.0921704	6.24	0.000	.3941249	.7554262
gini	.7784455	.4361592	1.78	0.074	-.0764108	1.633302
fdigdp	.0495995	.0099706	4.97	0.000	.0300575	.0691415
school	-.0026543	.003015	-0.88	0.379	-.0085636	.003255
openness	-.0070822	.0021765	-3.25	0.001	-.0113481	-.0028163
lifeexp	.008464	.0220104	0.38	0.701	-.0346757	.0516036
ocsedummy	.2443392	.1393666	1.75	0.080	-.0288143	.5174927
fertility	-.089249	.0721327	-1.24	0.216	-.2306264	.0521284
g	-.0106157	.0093498	-1.14	0.256	-.028941	.0077096
tertiaryedu	.0088223	.0031217	2.83	0.005	.0027039	.0149406
_cons	3.885259	1.470916	2.64	0.008	1.002317	6.7682

```
Instruments for differenced equation
        GMM-type: L(2/.).lngdpt
        Standard: D.gini D.fdigdp D.school D.openness D.lifeexp D.ocsedummy
                  D.fertility D.g D.tertiaryedu
Instruments for level equation
        Standard: _cons
```

Source: author's own elaboration

Figure 10: Sargan test (II)

```
Sargan test of overidentifying restrictions
        H0: overidentifying restrictions are valid

        chi2(5)      =  5.305735
        Prob > chi2  =    0.3797
```

Source: author's own elaboration

With the GMM Arellano-Bond estimation technique, we get a positive estimate of the coefficient relative to the variable which expresses inequality. This result, despite not being statistically significant at the 95% confidence level, is significant at the 90% level. In this case, the Sargan test still provide confirmation of the adequacy of the instrumental variables employed. The p-value of the test, in fact, is equal to 37.97%, well above the usual 5% threshold. On this basis it is thus not possible to reject the null hypothesis of the validity of the over-identifying restrictions. When the estimation is performed with the fixed effects method, in particular, we obtain a positive and statistically significant value of the estimated coefficient of $GINI_{t-1}$. In both estimates, all the three additional explanatory variables present an estimated coefficient whose sign is consistent with the expectations, even if only that relative to tertiary education is statistically significant at a 95% confidence level. With the random effects estimation method the estimated coefficient are for the most part not statistically significant; so for brevity the relative results are only reported in Appendix 4. In conclusion, even if the sign of the estimated coefficients tends to remain the same after the introduction of additional variables in the model, the quantitative impact of the single explanatory variables on the dependent variable, $Y_{i,t}$, presents a certain degree of sensitivity to the model formulation. The results obtained in the different estimates thus have to be considered with caution.

According to Castelló-Climent, "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" (Castelló-Climent 2007, p. 15).

5. Conclusions

In the present work the relationship between inequality and growth of *per capita* GDP has been examined. The three estimation techniques used (random effects, fixed effects and GMM Arellano-Bond) have provided empirical evidence of the existence of a positive relationship between the two variables of interest. It seems that higher inequality levels are associated to higher levels of *per capita* GDP and *per capita* GDP growth. It should not be overlooked, however, that the obtained results are not always statistically significant. Furthermore, the data used include a limited number of countries, which is mainly composed by advanced economies, and it is likely that the economic mechanism operate in a different way in the developed and in the developing countries. On this aspect, Kefi and Zouhaier highlight that: "despite the importance of empirical results […], deficiencies may arise: 1. Other possible mechanisms of the relationship under study were not considered. 2. Lack of data made our sample small. 3. The influence of the threshold level of economic development has not been tested" (Kefi and Zouhaier 2012, p. 1020).

Figure 11: Estimation results[13]

Explanatory variables	Random effects, full sample	Random effects, restricted sample	Fixed effects, full sample	GMM Arellano-Bond, full sample[14]	Fixed effect, full sample, model with additional variables	GMM Arellano-Bond, full sample, model with additional variables
$\ln(GDP_{i,t-1})$	-0.351*** (0.046)	-0.175*** (0.055)	-0.634*** (0.073)	0.664*** (0.059)	-0.715*** (0.077)	0.575*** (0.092)
$GINI_{i,t-1}$	0.284 (0.356)	0.107 (0.560)	1.225*** (0.458)	1.498*** (0.452)	0.933** (0.463)	0.778* (0.436)
$Open_{i,t}$	0.001 (0.001)	0.002* (0.001)	-0.002 (0.002)	-0.004* (0.002)	-0.004 (0.003)	-0.007*** (0.002)
$School_{i,t}$	0.004** (0.002)	0.001 (0.002)	0.004 (0.003)	-0.0001 (0.003)	0.002 (0.003)	-0.003 (0.003)
$Life_{i,t}$	0.035*** (0.011)	-0.011 (0.018)	0.017 (0.015)	0.025 (0.018)	-0.005 (0.021)	0.008 (0.022)
$FDI_{i,t}$	0.060 (0.011)	-0.007 (0.012)	0.028** (0.014)	0.045*** (0.012)	0.034** (0.014)	0.050*** (0.010)
$Ocse_{i,t}$	0.143** (0.067)	-0.001 (0.075)	0.015 (0.097)	0.143 (0.134)	0.108 (0.099)	0.244* (0.139)
$d_{1,i,t}$	0.207** (0.098)	-	-0.693*** (0.224)	-	-0.672*** (0.241)	-
$d_{2,i,t}$	0.019 (0.068)	-	-0.455*** (0.134)	-	-0.399** (0.157)	-
$d_{3,i,t}$	-0.009 (0.052)	-0.016 (0.052)	-0.241*** (0.074)	-	-0.202** (0.089)	-
$TertiaryEdu_{i,t}$	-	-	-	-	0.009*** (0.003)	0.009*** (0.002)
$Fertility_{i,t}$	-	-	-	-	-0.089 (0.072)	-0.142 (0.086)
$G_{i,t}$	-	-	-	-	-0.011 (0.009)	-0.005 (0.009)

Source: author's own elaboration

The present work finds evidence of a relevant impact of the level of inequality in the previous decade on the GDP growth rate in the subsequent decade within a certain country. As mentioned in the first section of this paper, in fact, Forbes (2000) by using the same estimation techniques, finds that a 1% variation in the Gini coefficient should be associated with a variation of the same sign between 0.13 and 0.36% in the average growth of *per capita* income in the next five years. According to the results shown in the previous sections, however, the impact of a 1% variation in the Gini coefficient should be followed by a variation of the same sign between 0.11 and 1.5% in the rate of GDP growth in the subsequent decade.

---

[13] The standard deviation is reported in parentheses; one, two or three * signal, respectively, that the obtained result is statistically significant at a 90%, 95% or 99% confidence level.

[14] As explained in the previous section, for the GMM Arellano-Bond estimation, the dependent variable is $\ln(GDP_{i,t})$, while in all the other cases it is $Y_{i,t} = \ln(GDP_{i,t}) - \ln(GDP_{i,t-1})$.

This non-negligible difference in the results can be at least partially explained by recalling that Forbes analyses five-years periods, while the present work employs ten-years averages. It is thus likely that the long term impact of inequality on economic growth is larger than the medium term one. In addition, Inequality data used by Forbes are taken from the 1996 Deininger and Squire dataset, while in the present work it has been possible to use the last updated version of that dataset, which includes more data and whose level of accuracy is higher. During the years many observations, regarded as less precise, have been eliminated and replaced with more reliable ones. As regards the methodology, fixed effects and GMM Arellano-Bond techniques allowed us to get estimates of the coefficient relative to $GINI_{i,t-1}$ which are statistically significant at a 99% confidence level, which is a quite satisfying result. However, some authors disagree about the opportunity of using ten-years average of the data; for example Pagano claims that: "[t]he difference between random-effect and fixed-effect results in assessing the effect of lagged inequality on growth may be due to the (arbitrary) choice of taking five or ten-year averages of Gini coefficients" (Pagano 2004, p.13). By using averages, a relevant part of data variability would be lost. In addition, it would be no more possible to make distinctions between the short-term, medium-term and long-term effects of income inequality on GDP dynamics. It would thus be preferable to use separately data concerning each year in each country. This theorical exigency is however often in contrast with the pratical problem given by the absence of annual recording of data about the Gini coefficient. Furthermore, given that the GMM Arellano-Bond utilizes as instrumental variables the lagged values of the endogenous variable of order superior or equal to two, if the time horizon were to be enlarged, the number of instruments could rise, thus probably increasing the quality of the estimates.
As regards possible future developments in this research field, first of all more explanatory variables could be added to the model, in order to further reduce omitted-variable bias problems. When choosing these variables, however, it should not be overlooked that for many World Bank indicators the recordings started in the '80s or '90s, so the risk is that of excessively limiting the time dimension (T) of the panel.
It would also be interesting to investigate in detail the differences between the relationship between inequality and *per capita* GDP in the developed and in the developing countries. For the latter, however, high quality data such that of the Luxembourg Income Study on the Gini coefficient are not available. Hoever, the last updated version of the Deininger and Squire dataset (which has been used in the present work) also contains several observations relative to Asian and African countries, starting from the '90s. In this case, as before, we face a trade-off between the dimensions N (countries) and T (time periods) of the panel we want to study. With today's available data, in fact, an enlargement of the number of countries necessarely implies a reduction of the time horizon considered and *vice versa*.
In the present work, a linear relationship between inequality and *per capita* GDP growth has been assumed; however, as explained in the first section of this paper, some authors claims instead that the relationship between the two variables of interest takes the form of an inverted "U".
Banerjee and Duflo (2003), for example, claim the existence of an inverted "U"-shaped relationship between GDP growth rate and the Gini coefficient. This means that, in a situation where inequality level is high, a reduction in the Gini coefficient has a positive impact on GDP

growth. On the contrary, where inequality level is already modest, a further reduction of the Gini brings about a reduction in the GDP growth rate.
Some authors, such as Barro (2003, 2008) and Pagano (2004), claim that the sign of the relationship between the inequality level and the growth rate of an economy depends on the level of *per capita* income. For low levels of *per capita* income, in fact, there seems to be a negative relationship between the two variables of interest, due to the transmission mechanisms linked to social and political instability. Once a certain ("threshold") level of development has been reached, however, the sign of the relationship would change, thus becoming positive. In this context, the transmission mechanism linked to savings and investment would prevail and a more unequal resource distribution would encourage physical as well as human capital accumulation.
A possible direction for future research consists in the estimation of a non-linear function that could better describe the existing linkages between inequality and growth. It would also be interesting to estimate the turning point in which the sign of the relationship changes. In conclusion, according to
Banerjee and Duflo: "[o]n the […] fundamental question of whether inequality is bad for growth […] some interesting evidence is beginning to trickle in, [but] we are only at the beginning of an enormous enterprise" (Banerjee and Duflo 2003, p. 296).

Appendix 1 – Countries and OCSE access year[15]

Country	Year
Australia	1971
Austria	1961
Belgium	1961
Canada	1961
Chile	2010
Korea, rep.	1996
Denmark	1961
Estonia	2010
Finland	1969
France	1961
Germany	1961
Japan	1964
Greece	1961
Ireland	1961
Israel	2010
Italy	1962
Luxembourg	1961
Mexico	1994
Norway	1961
New Zealand	1973
Netherlands	1961
Poland	1996
Portugal	1961
United Kingdom	1961
Czech Republic	1995
Slovak Republic	2000
Slovenia	2010
Spain	1961
United States	1961
Sweden	1961
Switzerland	1961
Turkey	1961
Hungary	1996

[15] Source: http://www.oecd.org/about/membersandpartners/list-oecd-member-countries.htm

Appendix 2 – Gini coefficient

I. Full sample (33 OCSE countries, 1961-2010), ten-years averages[16]

	1961-1970	1971-1980	1981-1990	1991-2000	2001-2010
Australia	0.287	0.242	0.337	0.369	0.361
Austria	n/a	0.279	0.290	0.267	0.312
Belgium	0.343	0.392	0.248	0.293	0.322
Canada	0.323	0.321	0.322	0.338	0.371
Chile	0.451	0.489	0.544	0.543	0.518
Korea, rep.	0.339	0.389	0.345	0.338	0.313
Denmark	0.350	0.338	0.243	0.287	0.290
Estonia	n/a	n/a	0.262	0.364	0.369
Finland	0.376	0.293	0.271	0.291	0.304
France	0.425	0.354	0.336	0.313	0.310
Germany	0.368	0.359	0.298	0.279	0.306
Japan	0.367	0.341	0.309	0.335	0.383
Greece	0.443	0.404	0.355	0.342	0.370
Ireland	n/a	0.364	0.390	0.338	0.354
Israel	0.371	0.363	0.397	0.389	0.415
Italy	0.396	0.381	0.330	0.342	0.350
Luxembourg	n/a	n/a	0.276	0.276	0.315
Mexico	0.528	0.509	0.509	0.527	0.471
Norway	0.324	0.301	0.326	0.308	0.298
New Zealand	0.568	0.446	0.334	0.361	0.380
Netherlands	0.397	0.290	0.306	0.302	0.304
Poland	0.254	0.241	0.236	0.305	0.364
Portugal	n/a	0.364	0.341	0.362	0.406
United Kingdom	0.260	0.265	0.329	0.356	0.381
Czech Republic	n/a	n/a	0.200	0.249	0.292
Slovak Republic	n/a	n/a	0.197	0.239	0.305
Slovenia	n/a	n/a	0.222	0.260	0.277
Spain	0.367	0.341	0.305	0.319	0.343
United States	0.419	0.409	0.397	0.403	0.412
Sweden	0.477	0.275	0.230	0.284	0.278
Switzerland	n/a	0.312	0.360	0.326	0.304
Turkey	0.533	0.482	0.494	0.445	0.435
Hungary	0.232	0.220	0.241	0.288	0.274

II. Restricted sample (28 OCSE countries, 1981-2010), ten-years averages [17]

[16] Author's own elaboration on the basis of the *World Income Inequality Database* (UNU WIDER 2014).

	1981-1990	1991-2000	2001-2010
Australia	0.292	0.308	0.317
Austria	0.227	0.270	0.269
Belgium	0.230	0.254	n/a
Canada	0.284	0.296	0.317
Denmark	0.255	0.227	0.228
Estonia	n/a	0.361	0.329
Finland	0.207	0.226	0.261
France	0.313	0.283	0.280
Germany	0.257	0.268	0.284
Japan	n/a	n/a	0.302
Greece	n/a	0.341	0.326
Ireland	0.328	0.327	0.305
Israel	0.309	0.321	0.366
Italy	0.314	0.330	0.330
Luxembourg	0.238	0.249	0.271
Mexico	0.441	0.480	0.453
Norway	0.234	0.236	0.256
Netherlands	0.251	0.244	0.266
Poland	0.271	0.289	0.312
United Kingdom	0.303	0.341	0.353
Czech Republic	n/a	0.231	0.266
Slovak Republic	n/a	0.220	0.260
Slovenia	n/a	0.231	0.238
Spain	0.302	0.345	0.318
United States	0.331	0.357	0.374
Sweden	0.205	0.234	0.237
Switzerland	0.309	0.294	0.271
Hungary	n/a	0.298	0.289

[17] Source: author's own elaboration on the basis of: *Luxembourg Income Study, Cross-National Data Center in Luxembourg.* http://www.lisdatacenter.org/data-access/key-figures/download-key-figures/ (14 February 2014). Five countries of the full sample have been excluded from the restricted sample: Chile, Korea Republic, New Zealand, Portugal and Turkey.

Appendix 3 – Data relative to the other explanatory variables

Country	*Period*	*FDI*	*Per capita GDP (t-1)*	*Per capita GDP (t)*	*Life exp.*	*School*	*OCSE dummy*	*Openness*
Australia	1991-2000	1.82	13361.16	20259.56	78.16	147.04	1	37.10
Australia	2001-2010	3.04	20259.56	34883.69	80.81	139.57	1	41.01
Austria	1981-1990	0.32	5984.86	13133.72	74.07	96.06	1	69.02
Austria	1991-2000	1.46	13133.72	25888.60	76.84	102.97	1	75.31
Austria	2001-2010	5.20	25888.60	37856.02	79.49	99.24	1	101.50
Belgium	2001-2010	15.79	24218.98	36335.70	79.11	121.69	1	153.17
Canada	1971-1980	1.97	2952.50	7793.35	73.84	91.31	1	46.48
Canada	1981-1990	0.87	7793.35	15704.39	76.42	96.56	1	50.76
Canada	1991-2000	2.46	15704.39	21237.05	78.19	103.38	1	68.16
Canada	2001-2010	3.00	21237.05	36265.52	80.25	101.89	1	68.61
Chile	1971-1980	0.66	746.56	1402.15	65.76	57.55	0	40.08
Chile	1981-1990	2.14	1402.15	1924.90	71.86	73.42	0	53.71
Chile	1991-2000	5.20	1924.90	4410.83	75.22	85.47	0	56.78
Chile	2001-2010	6.26	4410.83	8107.71	78.16	88.90	0	69.21
Czech Republic	1991-2000	4.60	3786.86	4991.41	73.47	89.08	1	100.15
Czech Republic	2001-2010	5.21	4991.41	13880.91	76.19	94.83	1	124.87
Denmark	1971-1980	0.38	2345.21	8560.90	73.95	97.57	1	61.97
Denmark	1981-1990	0.32	8560.90	16588.81	74.58	105.99	1	70.60
Denmark	1991-2000	4.66	16588.81	30963.91	75.67	117.80	1	73.35
Denmark	2001-2010	1.31	30963.91	47728.00	77.86	122.59	1	93.63
Estonia	2001-2010	10.95	3442.18	11158.29	72.65	102.88	0	149.12
Finland	1971-1980	0.14	1841.69	7051.02	71.84	99.71	1	53.09
Finland	1981-1990	0.31	6285.79	13498.71	74.43	105.62	1	53.70
Finland	1991-2000	2.64	15985.57	23628.82	76.46	118.22	1	63.70
Finland	2001-2010	3.81	23237.31	34043.12	78.96	115.61	1	78.38
France	1971-1980	0.43	2139.44	7051.02	72.98	81.27	1	38.46
France	1981-1990	0.59	7051.02	13498.71	75.43	87.36	1	44.97
France	1991-2000	1.85	13498.71	23628.82	77.93	110.06	1	46.67
France	2001-2010	2.77	23628.82	34043.12	80.41	108.47	1	53.35
Germany	1991-2000	1.67	13244.98	26170.43	76.66	99.45	1	51.86
Germany	2001-2010	1.19	26170.43	34356.70	79.08	99.44	1	78.38
Greece	1971-1980	0.69	948.07	3395.45	72.42	74.83	1	40.59
Greece	1981-1990	1.01	3395.45	6002.65	75.32	88.91	1	50.69
Greece	1991-2000	0.84	6002.65	11469.06	77.67	91.67	1	49.61
Greece	2001-2010	0.86	11469.06	22140.68	79.35	100.45	1	57.31
Hungary	1981-1990	1.68	1199.38	2345.50	69.31	87.67	0	75.14
Hungary	1991-2000	6.33	2345.50	4216.54	70.04	90.45	1	96.34
Hungary	2001-2010	12.49	4216.54	10643.66	73.03	97.95	1	146.37
Ireland	1981-1990	0.63	3363.29	8188.52	73.75	96.62	1	105.21
Ireland	1991-2000	7.58	8188.52	19570.71	75.70	109.01	1	140.47
Ireland	2001-2010	14.83	19570.71	45823.11	79.03	111.39	1	161.14
Israel	1971-1980	0.68	1454.02	3548.33	72.47	77.88	0	100.60
Israel	1981-1990	0.40	3548.33	7664.92	75.04	88.29	0	91.97
Israel	1991-2000	1.90	7664.92	16185.75	77.71	93.30	0	71.31
Israel	2001-2010	3.64	16185.75	22476.16	81.30	104.04	0	76.03
Italy	1971-1980	0.28	1396.20	4393.93	72.93	68.66	1	40.15
Italy	1981-1990	0.34	4393.93	11296.79	75.69	74.24	1	41.07
Italy	1991-2000	0.40	11296.79	20562.12	78.38	87.32	1	43.82
Italy	2001-2010	1.02	20562.12	30675.37	81.03	98.77	1	52.70
Japan	1971-1980	0.01	1108.13	5622.42	74.94	91.44	1	23.27
Japan	1981-1990	0.02	5622.42	16356.78	77.79	95.15	1	22.49
Japan	1991-2000	0.07	16356.78	35131.71	79.95	100.14	1	18.24
Japan	2001-2010	0.21	35131.71	35862.60	82.19	101.40	1	26.95
Korea, Rep.	1971-1980	0.14	156.92	940.20	64.11	57.05	0	55.40
Korea, Rep.	1981-1990	0.26	940.20	3517.94	68.83	89.11	0	61.26

Korea, Rep.	1991-2000	0.71	3517.94	10332.90	73.70	98.67	0	57.57
Korea, Rep.	2001-2010	0.90	10332.90	17782.63	78.57	97.12	1	76.82
Luxembourg	2001-2010	24.25	44359.09	82709.64	79.25	96.80	1	292.01
Mexico	1971-1980	0.72	502.38	1400.21	64.19	31.85	0	19.44
Mexico	1981-1990	1.15	1400.21	2377.56	68.97	53.39	0	30.86
Mexico	1991-2000	2.10	2377.56	4854.39	72.84	59.43	1	42.87
Mexico	2001-2010	2.79	4854.39	7927.87	75.61	79.14	1	54.54
Netherlands	1971-1980	1.18	1814.83	7559.39	74.71	86.04	1	94.72
Netherlands	1981-1990	1.76	7559.39	12977.83	76.41	106.17	1	109.29
Netherlands	1991-2000	5.32	12977.83	24113.39	77.49	128.39	1	115.38
Netherlands	2001-2010	5.41	24113.39	39896.56	79.47	120.80	1	132.82
New Zealand	1971-1980	1.43	2302.33	4822.82	72.29	80.21	1	52.84
New Zealand	1981-1990	3.29	4822.82	9893.80	74.22	84.69	1	56.37
New Zealand	1991-2000	4.15	9893.80	14837.00	77.09	107.51	1	59.10
New Zealand	2001-2010	1.77	14837.00	25419.33	79.80	118.13	1	60.85
Norway	1971-1980	0.91	2275.85	8742.79	74.95	88.99	1	76.96
Norway	1981-1990	0.55	8742.79	19126.76	76.17	96.35	1	74.00
Norway	1991-2000	1.95	19126.76	32798.52	77.83	114.85	1	71.83
Norway	2001-2010	2.97	32798.52	66807.66	80.02	113.41	1	71.45
Poland	1991-2000	2.67	1876.02	3486.36	72.15	94.70	0	48.18
Poland	2001-2010	3.80	3486.36	8802.05	75.10	99.54	1	75.52
Portugal	1981-1990	1.29	2098.11	4195.26	73.05	60.04	1	61.46
Portugal	1991-2000	2.03	4195.26	10972.62	75.17	95.50	1	61.72
Portugal	2001-2010	3.09	10972.62	18456.50	77.99	103.22	1	67.27
Slovak Republic	1991-2000	1.96	1552.78	4300.36	72.35	87.71	0	122.29
Slovak Republic	2001-2010	4.70	4300.36	12150.14	74.16	91.34	1	158.92
Slovenia	1991-2000	0.88	8698.90	8991.60	74.17	90.78	0	112.72
Slovenia	2001-2010	2.56	8991.60	18810.72	77.73	97.25	0	122.72
Spain	1971-1980	0.54	809.19	3357.74	73.56	69.97	1	28.81
Spain	1981-1990	1.46	3357.74	7102.46	76.38	95.49	1	37.56
Spain	1991-2000	2.46	7102.46	14649.99	78.09	111.40	1	46.33
Spain	2001-2010	3.71	14649.99	25818.92	80.46	117.18	1	56.88
Sweden	1971-1980	0.12	3160.21	9827.14	75.13	82.17	1	54.06
Sweden	1981-1990	0.50	9827.14	17956.24	76.87	88.09	1	63.62
Sweden	1991-2000	6.00	17956.24	28375.64	78.77	129.91	1	70.33
Sweden	2001-2010	4.68	28375.64	41036.38	80.63	114.17	1	89.38
Switzerland	1981-1990	1.14	10500.33	22600.56	76.71	94.57	1	71.33
Switzerland	1991-2000	2.47	22600.56	39098.88	78.67	98.29	1	71.50
Switzerland	2001-2010	5.08	39098.88	54196.71	81.29	94.94	1	88.85
Turkey	1971-1980	0.09	421.60	1168.63	55.74	32.20	1	14.46
Turkey	1981-1990	0.24	1168.63	1667.30	61.91	43.68	1	31.10
Turkey	1991-2000	0.43	1667.30	3276.86	67.33	60.88	1	40.90
Turkey	2001-2010	1.81	3276.86	7041.54	72.52	85.91	1	49.15
United Kingdom	1971-1980	1.47	1829.31	4792.23	72.81	80.29	1	52.30
United Kingdom	1981-1990	1.79	4792.23	11232.52	74.90	83.34	1	51.82
United Kingdom	1991-2000	3.16	11232.52	21565.09	76.92	98.30	1	53.22
United Kingdom	2001-2010	4.98	21565.09	36222.60	79.11	102.11	1	57.08
United States	1971-1980	0.22	3902.81	8650.01	72.51	84.87	1	15.47
United States	1981-1990	0.76	8650.01	18697.25	74.63	93.39	1	18.06
United States	1991-2000	1.32	18697.25	29861.73	75.98	93.63	1	21.98
United States	2001-2010	1.47	29861.73	43966.39	77.52	94.10	1	25.47

Source: author's own elaboration on the basis of the *World Development Indicators* (World Bank, 01.07.2014)

Appendix 4 – Estimation results[18]

I. Fixed effects, restricted sample (1981-2010)

```
Fixed-effects (within) regression               Number of obs      =        46
Group variable: country                         Number of groups   =        27

R-sq:  within  = 0.4925                         Obs per group: min =         1
       between = 0.7377                                        avg =       1.7
       overall = 0.5642                                        max =         2

                                                F(8,11)            =      1.33
corr(u_i, Xb)  = -0.9849                        Prob > F           =    0.3210
```

diff_ln	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lngdpt1	-1.064243	.5701779	-1.87	0.089	-2.319196	.1907097
gini	-.3236043	2.440069	-0.13	0.897	-5.694161	5.046952
fdigdp	.0387911	.0340576	1.14	0.279	-.0361692	.1137514
school	.0043008	.0098592	0.44	0.671	-.0173992	.0260008
openness	.0014314	.0067793	0.21	0.837	-.0134896	.0163525
lifeexp	-.0292899	.1622126	-0.18	0.860	-.3863174	.3277376
ocsedummy	.0695147	.2394416	0.29	0.777	-.4574926	.596522
d3	-.533655	.4422665	-1.21	0.253	-1.507077	.439767
_cons	12.49304	12.84147	0.97	0.352	-15.77083	40.75692

II. Random effects on the full sample with control variables

```
Random-effects GLS regression                   Number of obs      =       100
Group variable: country                         Number of groups   =        29

R-sq:  within  = 0.7795                         Obs per group: min =         2
       between = 0.4237                                        avg =       3.4
       overall = 0.6821                                        max =         4

                                                Wald chi2(13)      =    228.26
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

diff_ln	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lngdpt1	-.361342	.0532211	-6.79	0.000	-.4656535	-.2570305
gini	-.0124314	.3762557	-0.03	0.974	-.7498791	.7250162
fdigdp	.0014992	.0128716	0.12	0.907	-.0237288	.0267272
school	.0034976	.0021804	1.60	0.109	-.0007759	.0077711
openness	.0021943	.0012048	1.82	0.069	-.0001671	.0045556
lifeexp	.0400489	.0127392	3.14	0.002	.0150805	.0650173
ocsedummy	.1867271	.0740682	2.52	0.012	.0415561	.331898
fertility	.0255699	.0535179	0.48	0.633	-.0793233	.130463
g	-.0091457	.0058817	-1.55	0.120	-.0206736	.0023822
tertiaryedu	.0035027	.0019082	1.84	0.066	-.0002373	.0072427
d1	.3512157	.1169119	3.00	0.003	.1220727	.5803587
d2	.1396307	.0883561	1.58	0.114	-.033544	.3128053
d3	.0658501	.0649125	1.01	0.310	-.0613762	.1930763
_cons	.0642895	.8103307	0.08	0.937	-1.523929	1.652508

[18] Source: author's own elaboration

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