A Regional Perspective on Inequality and Growth in Portugal using panel cointegration analysis

Marta C. N. Simões[a]
João A. S. Andrade[b]
Adelaide P. S. Duarte[c]
[a]mcsimoes@fe.uc.pt(corresponding author); [b]jasa@fe.uc.pt; [c]maduarte@fe.uc.pt;
[a,b,c]GEMF – Grupo de Estudos Monetários e Financeiros;
Faculdade de Economia da Universidade de Coimbra;
Av. Dias da Silva 165, 3004-512 Coimbra, Portugal;
Tel. + 351 239790582; Fax. + 351 239790514

Abstract

This paper examines the relationship between inequality and economic growth for thirty Portuguese NUTS3 regions within a multivariate panel framework over the period 1995-2007 using panel cointegration techniques to test for the existence of a long-run equilibrium relation between inequality and output. The results show that there is a long-run equilibrium relationship between the variables, where the effect of inequality, measured as the Gini index of the earnings distribution, on output is negative. This negative influence seems to be determined by the behavior of the bottom of the earnings distribution, with the results pointing to the coexistence of a positive impact of inequality at the top of the distribution. However, when the regional productive structure is taken into account, specifically the importance of the agricultural sector, the sign of the relationship between inequality at the bottom of the earnings distribution and output becomes positive. In regions where agriculture employs a higher share of the workforce inequality seems to act as an incentive for workers to move to more productive sectors, manufacturing and services, and is therefore beneficial to growth. Additionally, the results confirm the predicted positive relationship between human capital and output. Another interesting result concerns the relationship between structural funds and output that point to a negative long run relation.

Keywords: inequality, economic growth, panel unit root tests, panel dynamic OLS

JEL classification: O12

1. Introduction

In light of the recent concerns over the high income inequality indicators for Portugal, on the one hand, and its dismal growth performance, on the other hand, the discussion on the relationship between inequality and growth in the Portuguese economy seems a timely one. According to the European Commission's report Employment and Social Developments in Europe 2011, in 2010 Portugal presented the fourth highest Gini coefficient of income distribution, after Lithuania, Latvia and Spain. Eurostat's data on real GDP per capita growth rates show that Portugal grew faster than the EU15 average between 1996 and 2000, respectively, 3.84% and 2.56% on average, but since 2001 its growth rate has become increasingly lower, respectively, 0.59% and 1.57% on average between 2001 and 2007, and its long-term growth prospects are quite poor. Additionally, the ongoing economic and public finances sustainability crisis with the associated cut in resources for social support increases the concerns with the long-term implications of potentially growing inequalities. We look at the inequality-growth nexus from a regional perspective examining the thirty Portuguese NUTS3 regions over the period 1995-2007 using panel cointegration techniques.

The analysis of the relationship between inequality and economic growth has received a great deal of attention over the years resulting in a large body of theoretical and empirical literature on the subject. At the theoretical level, four views on the relationship between inequality and growth are typically identified (see e.g Duarte & Simões (2011)[1]; Ehrhart (2009); Barro (2000); Aghion, Caroli, & García-Peñalosa (1999)). The first view, named by Aghion, Caroli et al. (1999)) as "traditional theories", postulates that inequality is good for growth due to its beneficial effects on savings, investment and incentives, with redistribution distorting incentives to save and work. The second view, the political economy approach, argues that greater inequality increases public support for redistribution, which leads to higher tax rates on capital accumulation and slower growth of the overall economy. The third view, called the credit markets imperfection approach suggests that barriers to financial markets access when, for instance, insufficient collateral leads some borrowers to forgo high-return projects, constitutes an impediment to capital accumulation and innovation so that

[1] A previous and longer version of this paper is available as Duarte, A. and Simões, M. (2009), "Channels of transmission of inequality to growth: A survey of the theory and evidence from a Portuguese perspective", GEMF Working Paper No. 07/2009.

higher inequality impedes growth. Finally, the political instability approach, the fourth view, defends that inequality amplifies the risks of social and political crisis with the inherent instability reducing investment and growth. However, García-Peñalosa (2008) argues that since output growth, from a supply-slide perspective, has four fundamental sources, physical capital, human capital, the labour supply and the level of technology, each of these represents a mechanism that relates the two variables, and so, depending on the source of growth, inequality and growth may be positively or negatively related.

Recent empirical studies have also failed to reach a consensus on the sign of the effect of inequality upon growth, arriving at varied and sometimes conflicting results (see e.g. Dominicis, Florax, & De Groot (2008)). In general, cross-country studies suggest that there is a negative relationship between initial income inequality and subsequent economic growth, even after controlling for other important growth influences, but using panel evidence leads to different conclusions. Forbes (2000) argues that this can be interpreted as evidence that inequality is detrimental to growth in the long run but not over shorter time horizons. In any case, most studies are interested in identifying a sign for the relationship revealing little about why inequality might impede or be conducive to economic growth (exceptions include Perotti (1996)).

Although the empirical literature on the relationship between inequality and growth is well established the empirical studies on this nexus for the Portuguese economy are rather limited. To the best of our knowledge such an analysis has been performed only by Andrade, Duarte, & Simões (2011) and Duarte & Simões (Forthcoming). This study extends the existing literature by adopting a regional perspective, examining the relationship within a multivariate panel cointegration framework which combines the cross-section and time series dimensions of the data. Individual country studies such as Andrade, Duarte et al. (2011) are often confronted with the problem of a short data span that lowers the power of traditional time series unit root and cointegration tests so adding the cross-sectional dimension can be important to increase the power of such tests. As in Duarte & Simões (Forthcoming), we follow Dominicis, Florax et al. (2008) suggestion that empirical studies on the relationship between inequality and growth should focus on using single-country data at the regional level[2]. This is because the inability of recent empirical studies to reach a consensus is rooted in data quality

[2] "The analysis of the growth inequality linkage on a regional basis may therefore be more informative than the analysis based on worldwide cross-country data." Dominicis, Florax and De Groot (2008), p. 676.

problems, sample coverage variations and the use of different estimation methods that can be mitigated, at least the first two, by taking a regional perspective of a specific country. This study also extends the existing literature by estimating the long run relationship between inequality and output using the Dynamic Ordinary Least Squares (DOLS) estimator that allows for consistent and efficient estimates of the long run coefficients and also deals with the problem of the endogeneity of the regressors, while accounting for the integration and cointegration properties of the data.

The remainder of the paper is organized as follows. Section 2 briefly overviews the hypotheses related to the inequality-growth nexus. Section 3 discusses the data, methodology, and empirical results. Section 4 offers some concluding remarks.

2. A brief overview of the literature on the inequality-growth nexus

Is inequality an impediment or a stimulus to economic growth? This is a recurrent debate in economic research. There is by now an extensive and rich literature on the relationship between inequality and economic growth that has been carefully and thoroughly surveyed by Benabou (1996), Perotti (1996), Aghion, Caroli et al. (1999), Barro (2000), G. Bertola, Foellmi, & Zweimuller (2006), García-Peñalosa (2008), and Ehrhart (2009), among others[3]. In the 1990's, a renewed interest on the subject took place that lead mostly to the development of theoretical models. Due to the scarcity of reliable and comparable data on inequality and due to the existence of poor measures of inequality, empirical literature on the subject lagged behind. The expected sign for the relationship between inequality and growth is a complex matter with early growth models on the subject predicting a positive sign, later ones arriving at a negative relationship and more recent growth models combining both effects. The evidence from empirical studies on the relationship between inequality and growth is also mixed. The cross-country studies usually find that higher inequality slows future growth, but the evidence from the studies that explore panel data is not compelling, pointing to an ambiguous effect of inequality on growth.

[3] Duarte & Simões (2011) provide a survey of the theoretical and empirical literature on two specific mechanisms of transmission from inequality to growth considered by the authors as the most likely to explain the relationship in the Portuguese economy.

According to some theories[4], also designated as traditional or classical theories on the impact of inequality upon economic growth, inequality promotes economic growth because: (i) growth depends positively on the accumulation of physical and human capital and richer individuals save more and thus invest more than poorer individuals and, in addition, there are indivisibilities and large sunk costs in physical capital investments implying a higher concentration of wealth in order to put into practice new investment projects; and (ii) it provides an incentive to the appearance of entrepeneurs/inventors expecting to belong to the wealthier part of the society, thus enhancing growth when innovation is the driving force of long run performance, as well as promoting higher effort by workers and thus efficiency (see e.g. Rodríguez-Pose & Tselios (2010)).

The negative effect of inequality on growth is justified on the basis of three main arguments or mechanisms of transmission. The fiscal approach literature is based on the interplay of two mechanisms, the political mechanism and the economic mechanism (see e.g. Giuseppe Bertola (1993); Alberto Alesina & Rodrik (1994), and Persson & Tabellini (1994). The political mechanism states that in more unequal societies the median voter will vote for higher levels of taxation and government expenditure. These introduce distortions which will in turn discourage private investment, hindering in this way economic growth – the economic mechanism.

The credit markets imperfection approach, also known as the borrowing constraints in human capital investments channel explains the relationship between inequality and growth based on the analysis of investments in human capital, that foster growth, when there are imperfections in credit markets. Only those individuals that have a high enough initial level of wealth are able to invest in human capital because borrowing is costly and difficult. Thus, an economy with a less unequal wealth distribution will be growth enhancing because it invests more in human capital. For instance, Oded Galor & Zeira (1993) show that in initially highly unequal societies, because of borrowing constraints, fewer individuals are able to invest in human capital, which in turn is detrimental to growth. O. Galor & Tsiddon (1994), on the other hand, develop a model in which the relationship between inequality and growth depends on the stage of development of an economy. At earlier stages of capitalism, the engine of growth is the accumulation of physical capital and a more unequal wealth distribution is beneficial to

[4] See e.g. Aghion, Caroli et al. (1999) and Barro (2000).

growth because the owners of capital have a higher propensity to save. At later stages of capitalism the engine of growth is human capital accumulation. If there are borrowing constraints on individual's human capital investment due to the existence of capital market imperfections to the borrowers, at later stages of capitalism a less unequal wealth distribution enhances economic growth because individuals decide to invest more in human capital.

The social-political instability channel argues that in more unequal societies individuals are more likely to be involved in activities that act as a disincentive to private investment, such as violent protests against the regime, coups or criminal activities, which in turn hinders capital accumulation and thus growth (see e.g. A. Alesina & Perotti (1996) and Perotti (1996)). This channel is potentially more relevant to explain the inequality-growth nexus in less developed countries but less likely to occur in a country like Portugal[5].

García-Peñalosa (2008) conducts a survey of the literature on inequality and growth focusing on recent theories especially suitable to explain this relationship in industrialized economies. She argues that both the sign and the direction of causation of the relationship depend on the source of growth under consideration, technological change, human and physical capital accumulation, and changes in the labour supply. The author also points out that "Given the conflicting theoretical predictions, we would like to turn to the empirical evidence in order to assess the relative importance of these various mechanisms." (p. 75), although so far that does not seem to have been made possible.

At the empirical level, a set of studies (see e.g. Persson & Tabellini (1994), Alberto Alesina & Rodrik (1994), A. Alesina & Perotti (1996), Clarke (1995), Perotti (1996), Deininger & Squire (1998), Chen (2003), Balisacan & Fuwa (2003), Bleaney & Nishiyama (2004)) tried to assess the contribution of inequality to cross-country variation in growth rates, after controlling for a number of variables that have been found relevant in the explanation of cross-country growth performance in a large number of empirical growth studies. The estimates of the impact of inequality on economic performance of most of the cross-country studies reveal a negative long-run relationship between the two variables, a result that is usually robust to different

[5] Duarte and Simões (2009) review in more depth the fiscal policy and the borrowing constraints on human capital investments channels based on the argument that they are the relevant ones to explain the relationship between inequality and growth in an economy like Portugal.

sensitivity analyses such as controlling for different inequality measures, different samples and time periods, the presence of outliers, model uncertainty, measurement error, reverse causation, and heteroscedasticity.

However, following the release of the Deininger and Squire inequality dataset[6] that assembled more reliable data with time series information for a large enough group of countries, a number of studies estimated the inequality and growth relationship using panel data techniques (see e.g. Persson & Tabellini (1994), Forbes (2000), Barro (2000), Banerjee & Duflo (2003), Voitchovsky (2005)), trying to uncover in this way a short to medium-term relationship. Contrary to the common message conveyed by most cross-country studies, the panel data evidence is quite diverse, finding either a positive, negative or non-existent correlation between inequality and growth.

In face of the mixed evidence on the inequality-growth relationship provided by empirical studies, Dominicis, Florax et al. (2008) use the statistical methodology known as meta-analysis, that combines the results of several empirical studies on inequality and growth to give a quantitative summary of the main findings, to survey the empricial literature (Dominicis, Florax et al. (2008), p.661). The analysis is based on 37 studies that give a total of 407 estimates for the coefficient of the inequality measure[7], restricted to be the Gini coefficient of income distribution[8]. The results show that the variation in the estimates of the income inequality-growth relation are systematically associated with differences in estimation methods, sample coverage and data quality – fixed effects estimates are usually higher, the negative impact is stronger in poorer countries and when the growth period analyzed is longer, and poorer data quality leads to lower coefficient estimates. A final quite relevant suggestion by the authors is that, "(…) it is particularly promising if attention would shift towards samples of regions within one country, or a limited set of countries with similar characteristics, or alternatively with different characteristics to the extent that these can be controlled for in the specification of the regression model." Dominicis, Florax et al. (2008), p. 678.

Malinen (2012) argues that the appropriate econometric methods to assess the relationship between inequality and growth are panel data time series methods since

[6] See Deininger & Squire (1996).
[7] See the citations in the previous paragraphs for examples of many studies included in this meta-analysis.
[8] The authors point out that "A remarkable feature is the wide range of the different effect size estimates. Approximately 65% of the estimates are negative (263 out of a total of 407), and approximately 35% (144) are positive." Dominicis, Florax and De Groot (2008), p. 662.

these do not imply any loss of information and allow for the identification of a long-run relationship between the variables by taking into account the time series properties of the data. The author applies panel cointegration methods to a sample of 53 countries with at most 25 annual observations per country to test for a long-run relationship between real GDP per capita and the Gini index of income distribution (as well as investment). The author finds evidence that the long-run relationship is negative in the sample as a whole and across different income groups (less developed, middle-income, and rich countries).

The regional dimension of the relationship between inequality and growth has been the focus of some studies. M. D. Partridge (1997), M. Partridge (2005), Panizza (2002) and Frank (2009) analyze evidence for the U.S. states[9]. Partridge (1997) and Panizza (2002) explore the panel structure of the data to uncover the sign of the relationship between inequality and growth. The first study considers ten-years growth episodes during the period 1960-90, finding a positive correlation between the Gini coefficient of income and growth, indicating a positive relationship between inequality and growth, but also a positive correlation between the income share of the middle quintile and growth, indicating a positive relationship between equality, not inequality, and growth. The second study uses state data from different sources covering a wider period (1940-80), Gini coefficients of income and the income share of the middle quintile, analyzes ten and twenty-years growth episodes, and uses different panel data techniques (pooled OLS, fixed effects, GMM), reaching the conclusion that the sign and significance of the estimated relationship changes when different measures of inequality are used and that controlling for outliers, serial correlation and structural breaks substantially changes the results. Partridge (2005) resumes the same issue for the period 1960-2000, estimating a short-term model with data averaged for 10 years periods and a long-run model in which 1960-2000 growth is regressed on the initial values of the explanatory variables, namely the initial Gini coefficient of income and the initial middle-quintile share. The results show a positive correlation between the middle-class share and overall inequality and long-run growth but the short-term results (associated with fixed effects estimations) are ambiguous with no definite conclusion possible. Frank (2009) uses state-level annual data over the period 1929-2000 to determine whether the income

[9] Fallah & Partridge (2007) also analyze the inequality-growth relationship for the U.S. but using county data (not state data) for the 1990's. The authors find a positive correlation in urban areas but a negative one in nonmetropolitan areas.

share of the top decile Granger causes income growth and to determine the sign of the relationship. The results confirm that inequality causes growth and give evidence that an increase in the income share of the top decile reduces future income growth but with regional differences – the relation is stronger for the more densely populated states.

Arbia, Dominicis, & Piras (2005), Ezcurra (2007) and Rodríguez-Pose & Tselios (2010) investigate the link between inequality and regional growth from the perspective of the EU. The first two studies apply spatial econometrics techniques. Arbia, Dominicis and Piras (2005) use regional data at NUTS II level for the period 1977-2002 dividing the sample into non-transition and transition European countries. For the sample without transition countries regions, the effect of income inequality on growth is positive and significant, but being located close to regions with a high level of income inequality is detrimental to a region's growth performance. The same conclusions apply when data for the transition countries regions are introduced indicating that while inequality within a country is growth enhancing, unequal realities in the neighbours have a detrimental impact. Ezcurra (2007) examining 63 NUTS I and II EU regions over the 1993-2002 period and using information from the European Community Household Panel (ECHP) to build income inequality measures, on the other hand, arrives at a negative relationship between a region's income dispersion and growth. Rodríguez-Pose and Tselios (2010) assess the contribution to regional growth of both income and education inequalities, again using data from the ECHP between 1994 and 2001 to compute dispersion measures for both distributions. The results indicate that both income and educational inequality matter for regional growth and have a positive impact upon it, although relatively small.

3. Data, methodology, and results

To investigate the relationship between inequality and growth we use the following model:

$$ly_{it} = \alpha_i + \delta_i years + \beta_{1i} lineq_{it} + \beta_{2i} lh_{it} + \beta_{3i} lasf_{it} + \beta_{4i} e\_sector_{it} + \varepsilon_{it} \qquad (1)$$

where i=1,…,N for each region in the panel and t=1,…,T refers to the time period; *years* denotes an homogenous trend; *ly*, *lineq*, *lh*, and *lasf* are the natural logarithms of real output per capita, an earnings inequality measure (respectively, *lgini*, *lr1050*, and *lr9050*), the average number of years of education of the workforce, total or relative to a certain schooling level (respectively, *lh* – total; *lhs* - secondary, and *lhh* - tertiary), and the ratio of structural funds received relative to GDP, respectively, and *e_sector* is the employment share of one of the three major sectors of activity, agriculture, industry and services (respectively, *e_Agr*, *e_Man*, and *e_Ser*). The parameters α_i and δ_i allow for the possibility of region-specific effects and deterministic trends, respectively. ε_{it} denote the estimated residuals which represent deviations from the long-run relationship. Equation (1) is to be considered as a long-run or equilibrium relation and since all variables are expressed in natural logarithms the respective coefficients can be interpreted as elasticities (except for the coefficients of the sectoral employment shares).

The choice of the explanatory variables, besides inequality, was determined by theoretical predictions, the convenience of a parsimonious specification and the availability of regional data for the Portuguese NUTS3 regions. Human capital, measured in many empirical growth studies by educational attainment, is expected to influence positively regional growth performance not only due to its role as an ordinary input into production but also as a major input in the production of new ideas (see e.g. Mankiw, Romer, & Weil (1992); Benhabib & Spiegel (1994, 2005); Sianesi & van Reenen (2003)Sianesi & van Reenen (2003)Sianesi & van Reenen (2003)Sianesi & van Reenen (2003)Sianesi & van Reenen (2003)Sianesi & van Reenen (2003)). The influence of the sectoral composition of regional economic activity has also been considered has a relevant regional growth determinant in previous studies (see e.g. Ezcurra (2007)). Although investment ratios have been found to be one of the more robust growth determinants (see e.g. Levine & Renelt (1992), and Sala-i-Martin (1997)) this series is not available at NUTS3 level for Portugal. This problem may be to some extent overcome by the fact that we include the structural funds Portuguese regions received from the EU during the period under analysis as an explanatory variable, at least assuming that they have been used primarily for investment.

3.1. Data

Data for this study refers to five variables: real GDP per capita, an earnings inequality measure, average years of schooling, a measure of the regional productive structure, and the ratio of structural funds received relative to GDP. Annual data from 1995 to 2007 were obtained mainly from the Regional Accounts of the Portuguese National Statistics

Office (*INE*) and the Personnel Records (*QP*[10]) database[11], a rich Portuguese dataset with detailed and comprehensive information on workers and firms, which is the result of an annual compulsory survey conducted by the Ministry of Solidarity and Social Security *(*MSSS*)* where firms are required to provide information about their workers on items such as monthly compensation, highest schooling level attained, age, tenure and monthly hours worked[12]. The length of the period selected was dictated by data availability on regional accounts. Given the short time span of the data we compile it within a multivariate panel data framework.

Regional real output per capita corresponds to per capita GDP in year 2000 euros computed using data from the Regional Accounts of *INE*[13] and the Department of Prospective and Planning (DPP) of the Ministry of Environment[14]. The data concerning the regional productive structure, measured as the regional employment share in agriculture, manufacturing or the services sectors was also obtained from *INE*. The ratio of structural funds received relative to GDP was computed with data from *INE* and the *Financial Office for Regional Development* (*IFDR*). Structural funds refer to the amount received, per year, by each Portuguese NUTS3 region from FEDER, the European regional development fund, relative to regional GDP[15].

To measure earnings inequality and average years of schooling[16] of the workforce at the regional level in Portugal we use data from the *QP* database. Earnings inequality[17] measures are computed based on the analysis of two variables: average earnings[18] of the employees working full time and the number of employees distributed according to the

---

[10] *Quadros de Pessoal*, in Portuguese.
[11] Data provided by GEP-MSSS.
[12] *QP* database does not include public sector workers and the self-employed.
[13] Regional accounts for the Portuguese economy at the NUTS3 level are available, on a comparable basis, from 1995 until 2010 (predicted values). We chose to limit our analysis to the 1995-2007 period in order not to capture potential effects of the 2007-08 financial crisis.
[14] We thank Natalino Martins from DPP for providing us data on Gross Value Added in year 2000 Euros that allowed us to compute regional price indexes. See also Martins & Barradas (2009).
[15] Structural funds are given in 10^3 euros and GDP in 10^6 euros.
[16] See Fidalgo, Simões, & Duarte (2010) for details on the construction of the variable average years of total schooling of the workforce at the regional level. Average years of schooling of the workforce by schooling level, secondary and tertiary, were taken from Cardoso & Pentecost (2011), which also use data from *QP* database.
[17] "Wage income is the main source of personal and household income, and hence its distribution has major implications for inequality. A large literature has hence examined the evolution of the distribution of labour earnings, and documented that in the last two decades of the 20th century a number of industrialised countries experienced a substantial widening in the earnings distribution." García-Peñalosa (2008), p. 61.
[18] This is a monthly average reported each year referring to the month of October. We consider average full earnings of the employees that performed complete working hours during the month of October.

economic activity of firms and the level of education of employees. The methodology used to assess earnings inequality at the regional level is the Lorenz dominance analysis (see e.g. (Fields (2001)). For each region we constructed weighted distributions of earnings from which we compute the inequality measures to be used in the estimations: the Gini index (Xu (2004)), and the ratios between percentiles 90% and 50% (*r9050*) and between percentiles 10% and 50% (*r5010*), that provide information on the impact of inequality in different parts of the distribution, top and bottom, respectively. Previous studies show that the relation between inequality and output might depend on inequality in different parts of the distribution, top or bottom, with inequality at the top fostering faster growth due for instance to the incentives argument, and inequality at the bottom reducing the growth rate because it leads to less investment in human capital (see e.g. Voitchovsky (2005) and García-Peñalosa (2008))[19].

3.2. Methodology

Our empirical investigation of the relationship between inequality and growth in the Portuguese NUTS3 regions is conducted in two steps. First, we test for the order of integration of the variables. Second, we estimate long-run coefficients using the dynamic OLS (DOLS) panel cointegration estimation methodology.

Unit root testing in panels is quite recent (see e.g. Baltagi (2005)). In what follows, we provide a short description of some tests that assume cross-sectional independence and of a test proposed by Pesaran that assumes the presence of cross-sectional dependence. Afterwards, we also provide a short description of a stationarity test.

The simplest model for testing panel unit roots was a mere replication of a time series unit root test, based on the following equation:

$$y_{i,t} = \delta_0 + \alpha \cdot y_{i,t-1} + \mu_{1,t}\,,\ \ i = 1,\ \ldots, N\,,\ t = 1,\ \ldots, T\,,\ \mu_{i,t} \sim iid(0,\sigma^2) \tag{1}$$

without or with a constant term (see Quah (1994) and Quah (1996)), where the null is H_0: $\alpha=1$ against the alternative H_a: $\alpha \le 1$. Levin & Lin (1992) and Levin & Lin (1993) add individual and time specific components to equation (1), so that:

$$\mu_{i,t} = \delta_1 \cdot t + \eta_i + v_t + \varepsilon_{i,t}\,,\ \varepsilon_{i,t} \sim iid(0,\sigma^2) \tag{2}$$

[19] According to García-Peñalosa (2008), p. 75: "Inequality has two effects on the growth rate, a positive incentive effect, in line with the traditional literature, and a negative opportunity-creation effect operating through the constraints on human capital investment that it imposes on poor individuals. Greater inequality is hence conducive to growth if it occurs at the top of the distribution, and detrimental if it occurs at the bottom."

where the correction for serial correlation is done in the same way as that employed in traditional ADF time series test. The authors also prove that the panel tests statistics have limiting Normal distributions.

The major limitation of these tests is the exclusion of heterogeneity by imposing a value of α common to all individuals (*i=1,…,N*). Im, Pesaran, & Shin (2003)[20] (henceforth IPS) propose a test that allows for heterogeneous individual behavior. Supposing that t_a (*i=1,…,N*) are the t-statistics associated with each cross-section estimation then $Z = \sqrt{N} \cdot \frac{t_\alpha - \mu}{\sigma} \sim N(0,1)$, $t_\alpha = \frac{1}{N} \cdot \sum_{i=1}^{N} t_{\alpha_i}$, $\mu = E[t_{\alpha_i}]$, and $\sigma^2 = Var(t_{\alpha_i})$. The null, $H_{0,}$ is that all series contain a unit root against the alternative, null is H_a, that some of the individuals are stationary.

Harris & Tzavalis (1999) (henceforth HT) propose a unit root test in a fixed effects panel model, with or without time trend, taking *T*, the time dimension, as fixed. This test is appropriate for small *T* data samples, i.e. with few time series observations. The authors demonstrate the convergence property of the desirable statistic $\sqrt{N} \cdot (\alpha - 1 - B) \to N(0,C)$, with $B = \frac{-3}{T+1}$, $C = \frac{3 \cdot \left(17 \cdot T^2 - 20 \cdot T + 17\right)}{5 \cdot (T-1) \cdot (T+1)^3}$, and by appropriate standardization we have the usual *N(0,1)* distribution. However this HT test assumes homogeneity, which might constitute a problem. The null, H_0 , corresponds to the usual hypothesis of a unit root for all the data.

All these tests assume cross-section independence which goes against our perception that individuals, often regions and/or countries, are interdependent. Pesaran (2007) proposes a method to solve this problem of cross-section dependence that arises due to unobserved common factors. The equation corresponding to this Cross-Section Augmented Dickey-Fuller (CADF) for each individual is given by:

$$\Delta y_{i,t} = \delta_i + \alpha_i \cdot y_{i,t-1} + c_i \cdot \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \epsilon_{i,t}, \text{ where } \bar{y}_t = \frac{1}{N} \cdot \sum_{i=1}^{N} y_{i,t} \qquad (3)$$

Pesaran suggests to proxy the common factors with the individual mean ($\bar{y}_t$). We omitted lags of the dependent variable to solve eventual serial correlation problems for each individual. The cross-sectionally augmented IPS (CIPS) is given by:

$$CIPS = \frac{1}{N} \cdot \sum_{i=1}^{N} t_{\alpha i}$$

[20] First published in June 1995.

where the appropriate critical values are calculated in Pesaran (2007).

Hadri (2000) proposes an adaptation of the KPSS LM test for time series (Kwiatkowski, Phillips, Schmidt, & Shin (1992)) to panel data. Suppose that the Data Generating Process can be represented by:

$$y_{i,t} = \delta_i \cdot t + r_{i,t} + \epsilon_{i,t}\ ,\ \epsilon_{i,t} \sim iid(0, \sigma_\epsilon^2) \tag{4}$$

where $r_{i,t}$ is a random walk, $r_{i,t} = r_{i,t-1} + \mu_{i,t}$, $\mu_{i,t} \sim iid(0, \sigma^2)$. Under the null hypothesis of stationarity around a level or a trend ($\delta_i \neq 0$), $\sigma_\mu^2 = 0$, or $\dfrac{\sigma_\mu^2}{\sigma_\epsilon^2} = 0$, against the alternative $\dfrac{\sigma_\mu^2}{\sigma_\epsilon^2} > 0$. The LM statistic is obtained by $LM = \dfrac{\sum_{i=1}^{N}\sum_{t=1}^{T} S_{i,t}^2}{\hat{\sigma}_\epsilon}$, $S_{i,t} = \sum_{h=1}^{t} \hat{\epsilon}_{i,t}$, assuming $\hat{\sigma}_\epsilon^2$ is a consistent estimator of $\hat{\sigma}^2$.

In the presence of unit root variables Kao & Chiang (2001) demonstrate that the OLS estimator has a considerable bias in normal samples and that, in general, the FMOLS (fully modified OLS) estimator does not improve the OLS estimator. The autors conclude that the DOLS (dynamic OLS) estimator performs better than the other two estimators even if the limiting distribution of the regressors is the same for the DOLS and FMOLS estimators. Both the FMOLS and the DOLS estimators are supposed to correct for endogeneity and serial correlation. The Kao-DOLS approach is a derivation of Saikkonen (1991) for panel data where the observations for each unit are corrected using estimators of the long-run conditional variances and it is supposed that there is no cross-sectional dependence. Mark & Sul (2003) propose to weight the observations of each individual with an estimate of the asymptotic covariance matrix. Their approach requires a two steps DOLS. Both the Kao & Chiang (2001) and the Mark & Sul (2003) estimators consider fixed effects in the estimation of the cointegration regression, and so the latter authors argue that the expression "dynamic least squares dummy variable" is more accurate to designate these estimators although, for simplicity, they use the more commonly used designation DOLS.

For a homogeneous estimation, the β_{DOLS} coefficients are obtained from regression (5):

$$y_{i,t} = \alpha_i + x_{i,t}^{'} \cdot \beta + \sum_{j=-q}^{q} c_{i,j} \cdot \Delta x_{i,t+j} + \dot{v}_{i,t} \tag{5}$$

with $\dot{v}_{i,t} = v_{i,t} + \sum_{|j|>q} c_{i,j} \cdot \varepsilon_{i,t+j}$, where ε has the usual i.i.d. properties.

Mark & Sul (2003) propose a homogeneous cointegrating vector but the presence of individual-specific fixed effects and individual-specific time trends are allowed and the cross-sectional dependence is corrected by time-specific effects.

3.3. Results

Tables 1-4 present the results of the different panel unit root tests described in the methodology section for both the levels and the first differences of the variables, all in logs. For the IPS test we have removed the individual means in order to control for cross-sectional correlation. In this case, the two relevant statistics to determine whether the series have a unit root are the "t" and "Z" statistics without trend and with trend. The null hypothesis admits that all series contain a unit root and the alternative that some fraction of individuals/regions is stationary. The "Z" statistic of the HT test considers as the null that the entire sample has a unit root. The "t" statistic of the CADF test considers as null that all individual values have a unit root against the alternative that some fraction of individuals are stationary. The constant is present in the first, and in the second with the trend. The Hadri "Z" test considers as the null hypothesis the stationarity of all individuals against the alternative that some fraction of individuals has a unit root. We use a Bartlett kernel with one lag to control for serial correlation.

[Insert Tables 1-4 here]

As for the results concerning the variables in levels, according to the IPS unit root test results we can conclude: (i) that all the inequality variables (*lgini*, *lr1050*, and *lr9050*) are stationary; (ii) that *lhh* is stationary around a trend; and (iii) for the presence of a unit root in all the other variables. These results are confirmed by the HT test, although in this case without a trend for *lhh*. The results for the CADF unit root test lead to the rejection of the null hypothesis of a unit root for all the inequality variables, as in the former tests, and also for the variables *ly* and *e_Ser* around a trend. The results for the Hadri panel unit root test allow us to reject the null hypothesis of stationarity for all the variables. Concerning the variables in first differences, the IPS and HT tests allow us to reject the presence of a unit root for all variables. The results with the CADF panel unit root test do not lead to the rejection of the presence of a unit root for the variables *de_Agr*, *dlhs*, and *dlhh*. The results with the Hadri panel unit root test reject the null hypothesis of stationarity for *dlh*, *dlhs* and *dlhh*. Based on the previously described results for the different panel unit root tests we consider that the hypothesis that all variables in levels have a unit root is a reasonable one, notwithstanding some of these results are somewhat contradictory.

Given that the panel unit root tests indicate that each variable is integrated of order one, the dynamic OLS (DOLS) technique is used to estimate the long-run equilibrium relationship. We used two different methodologies in our DOLS estimations, that of Kao & Chiang (2001) and that of Mark & Sul (2003). The latter considers four different behavioral hypotheses: "no time trend, no common time effect; "no time trend, with common time effect"; "heterogenous time trend, no common time effect"; and "heterogenous time trend, common time effect". In all four estimations using the Mark (2003) methodology that we carried out the results did not seem to make economic sense. For instance, we got negative and significant coefficients on human capital and substantial differences in coefficient values across regressions corresponding to the different behavior hypothesis. We thus present only the results obtained with the Kao (2001) DOLS estimation methodology (Tables 5-7). All variables are in logs except for the variable "years" that represents a homogeneous trend. Tables 5-8 present the results of panel cointegration estimation of the regression equation using the DOLS estimation methodology and considering different inequality measures. To carry out the estimations we used the procedure *xtdolshm* for Stata 11.0 (see Amadou (2010)) assuming one lead and one lag.

[Insert Table 5 here]

Table 5 exhibits the results of panel cointegration estimation using the Gini index as the earnings inequality measure. Regressions 1-8 consider average years of total schooling, *lh*, as the human capital measure. Regressions 9-12 consider that the relevant schooling level for production is secondary schooling and so the proxy used for human capital is average years of secondary schooling, *lhs*. In regressions 13-18 it is considered in addition the contribution of tertiary schooling by introducing simultaneously average years of tertiary schooling, *lhh*, as an explanatory variable. In each case, we first tested for the long-run relationship between output, the human capital variable(s) and the inequality measure, without and with the homogeneous trend 'years'[21]. The next step was to include structural funds, *lasf*, as an additional

[21] The idea behind starting with this model with a smaller number of variables than those present in equation (1) was to test for the sign and significance of the trend variable in order to check whether our fundamental explanatory variables, human capital and inequality, would in reality be capturing this effect.

explanatory variable, and finally considering the influence of the regional productive structure by introducing the employment shares of the three major sectors of activity, one at a time or combined, depending on the statistical significance of the results.

The results in Table 5 point to a negative relationship between earnings inequality and output when measured as the Gini index of the employees earnings distribution. The estimated coefficient of *lgini* is in most regressions negative and statistically significant so that an increase in inequality reduces output. There are however some exceptions to this result in our eighteen regressions considering the Gini index, regressions 5, 8, 10, 12 and 18. These regressions have in common the presence of *e_Agr*, the proxy for the importance of the agricultural sector, in terms of employment, in each region over the period under analysis, as an explanatory variable. The estimated coefficient for this variable is negative and statistically significant so that when we take into account the negative influence of agricultural activities on output, an increase in employees' compensation inequality now has a positive influence on output. Equations 5, 8, 10, 12 and 18 provide statistically significant empirical evidence that the smaller the dependence of GDP on agriculture and the higher the inequality expressed by higher earnings in industry and services, the higher real per capita GDP will be. A possible economic explanation for this change in the sign of the results concerning the inequality measure is the higher marginal productivities of labour in the manufacturing and services sector relative to the agriculture sector, with higher earnings inequality creating an incentive to work in the manufacturing and services sector. Since the latter are more productive than agriculture, an increase in inequality will increase regional output.

As far as the other explanatory variables are concerned, the human capital regressors are positive and statistically significant in all the regressions presented in Table 5, lending support to both the exogenous and endogenous growth models predictions on the importance of human capital for production both as inputs in the production of final goods and in the production of technology, although our empirical model does not allow us to distinguish between the two mechanisms. An indication of the importance of human capital as an input in the production of technology is the fact that when we consider the separate influence of *lhs* and *lhh* the estimated coefficient on average years of tertiary schooling, the educational attainment level potentially more important for this task, is positive and statistically significant, although quantitatively lower than the *lhs* coefficient. The trend variable 'years' has an unambiguous negative and statistically significant sign, which is not surprising since we know from national/aggregate data that output growth stopped in 1988 and the stagnation in terms of trend output began in 2002. Another interesting result is the negative and statistically significant coefficient of the structural funds variable in all regressions. Although we should expect a negative influence running from output to structural funds transfers (richer regions receive less funds) since some years after the beginning of these transfers it is natural to register a reduction in output differentials, the presence of a long run negative relation points to the null impact of these transfers in the reduction of output differentials. Finally, in what concerns the regional productive structure, there is clear evidence of a positive relation between the importance of the services sector and output, and of a negative relation between agriculture and aggregate output. In addition, the presence of a strong agricultural sector represents an important negative impact on total output and this effect is quantitatively very close to the positive effect resulting from the services sector. As for manufacturing, although positive the estimated coefficient on the manufacturing employment share variable is not statistically significant.

[Insert Table 6 here]

The results of panel cointegration estimation using the ratio of percentile 10^{th} relative to percentile 50^{th} as the earnings inequality measure are presented in Table 6 since previous studies show that the relation between inequality and output might depend on inequality in different parts of the distribution, top or bottom. In this case we consider specifically the relation between inequality at the bottom of the distribution and output. An increase in the *r1050* variable corresponds now to a decrease in inequality, so that the confirmation of the previous results with the Gini index requires a positive estimated coefficient for this inequality measure. The consecutive regressions follow the same logic as that presented in Table 5. Regressions 19-26 consider average years of total schooling, *lh*, as the human capital measure, while regressions 27-32 consider that the relevant schooling level for production is specifically secondary schooling measured as average years of secondary schooling, *lhs*. Regressions 33-38 consider the separate and additional contribution of average years of tertiary schooling, *lhh*. We first tested for the long-run relationship between output, the human capital variable(s), the inequality measure, and the structural funds variable, without and with the homogeneous trend. Next, the influence of the regional productive structure was considered.

From the inspection of the results presented in Table 6 we can see that the estimated coefficient of *lr1050* is in general positive and statistically significant. To be more precise, it is positive in sixteen regressions out of the total of twenty estimated in this case, pointing to, as was the case with the results with the Gini index, to a negative relation between inequality and output. Moreover, regressions 23, 26, 30 and 32, the cases when the estimated coefficient is negative, are again the regressions where the agriculture employment share is included, the same situation we have already found with *lgini* when the estimated coefficient of the inequality variable changed its sign. The same conclusions also apply to the estimated coefficients for the remaining explanatory variables.

[Insert Table 7 here]

Table 7 presents the results of panel cointegration estimation using the ratio of percentile 90th relative to percentile 50th as the earnings inequality measure. In this case, we are controlling for a different sign of the relation between inequality and output at the top of the earnings distribution. An increase in the *r9050* variable corresponds again to an increase in inequality, as in the Gini index case. Again the different regressions can be grouped in three main types according to the human capital variable(s) considered. Regressions 39-44 consider average years of total schooling, *lh*, as the human capital measure; regressions 45-50 consider average years of secondary schooling, *lhs*; and, finally, regressions 51-56 consider in addition average years of tertiary schooling, *lhh*. In each of the three groups of regressions, we first tested for the long-run relationship between output, the human capital variable(s), the inequality measure, and *lasf*, the structural funds variable, without and with the homogeneous trend. Finally, the influence of the regional productive structure was considered.

The results in Table 7 point to an interesting change in terms of the evidence on the relationship between earnings inequality and output relative to the results obtained with Gini index and the ratio of percentile 10th relative to percentile 50th. When the *lr9050* variable is used as the inequality measure, in only two out of the eighteen regressions the estimated coefficient is negative and statistically significant, the result that at first sight would confirm the evidence we got based on the other two inequality measures. In the vast majority of the regressions the estimated coefficient of this inequality measure is positive and statistically significant indicating that an increase in inequality is beneficial to growth. This result however does not invalidate the previous ones. In fact, they are compatible. As shown by Voitchovsky (2005), different mechanisms can be working at the same time so that an increase in inequality at the bottom of the earnings distribution will decrease output, while an increase in inequality at the top has the opposite effect. Inequality is good for growth since richer individuals have higher marginal propensities to save, thus leading to higher capital accumulation, and because it creates an incentive to belong to the wealthiest classes of society leading to higher working effort, both resulting in faster growth, but this only happens when inequality increases at the top of the distribution. If inequality increases at the bottom of the distribution, it will prevent an increasing number of poor but talented individuals to invest in human capital, and in this way hurt growth. Contrary to the results concerning the inequality measure, the conclusions regarding the remaining explanatory variables do not change when compared to the results presented in Tables 5 and 6.

[Insert Table 8 here]

Based on the evidence from the two previous tables, 6 and 7, in Table 8 we present the results of the estimations considering both inequality ratios at the same time (regressions 57-79) in order to confirm separate influences from different parts of the earnings distribution. Again the regressions are grouped according to the human capital variables considered. The results point to a negative influence of inequality at the bottom of the earnings distribution, together with a positive influence of inequality at the top. Exceptions to this result can be found in equations 60, 63, 69, 72, and 77, when the influence of the agricultural sector is considered. In this case, as was the case in Table 6, the estimated coefficient of the ratio of the 10^{th} percentile relative to percentile 50^{th} becomes negative so that an increase in inequality (corresponding to a decrease in *lr1050*) has a positive effect on output. The sign of the estimated coefficient of the ratio of the 90^{th} percentile relative to percentile 50^{th} does not change. As for the other explanatory variables, the same conclusions as in Tables 5-7 apply.

4. Conclusions

Although Portugal ranks as one of the most unequal countries (in terms of income distribution) relative to other EU member states, inequality has hardly ever been considered as an explanatory factor in the studies that aim at explaining economic growth in the Portuguese economy, including studies devoted to the analysis of regional growth. To fill this gap, this paper investigated the relationship between inequality and economic growth, using panel cointegration estimation techniques. The empirical analysis of this study exploits annual panel data on 30 Portuguese NUTS3 regions and the sample period runs from 1995 to 2007. Various panel unit root tests were conducted to demonstrate that the data variables are integrated processes with unit roots. The

DOLS (dynamic OLS) panel cointegration estimation technique was employed to estimate the regression equation.

Overall, the results show that the distribution of earnings and output seem to have a long-run equilibrium relation, as predicted by theoretical models, and that the sign of the relationship might vary according to the earnings groups affected by changes in inequality, so that different transmission mechanisms might be working simultaneously. Specifically, we found that an increase in inequality depresses longer-term growth most likely by dampening investment in human capital, but this negative sign coexists with a beneficial growth impact of inequality at the top of the earnings distribution, supporting the incentives argument. However, when the regional productive structure is taken into account, specifically the importance of the agricultural sector, the sign of the relationship between inequality at the bottom of the earnings distribution and output becomes positive. In regions where agriculture employs a higher share of the workforce inequality seems to act as an incentive for workers to move to more productive sectors, manufacturing and services, and is therefore beneficial to growth. These results call for caution when designing redistribution policies at the regional level. Additionally, the results confirm the predicted positive relationship between human capital and output. Another interesting result concerns the relationship between structural funds and output that point to a negative long run relation.

A better understanding of the overall effect of inequality on growth involves future research on the empirical assessment of the different channels through which inequality in different parts of the distribution may influence the growth process. These channels are surely important from a redistributive policy design perspective.

References

Aghion, P., Caroli, E., & García-Peñalosa, C. (1999). Inequality and economic growth: the perspective of the new growth theories. *Journal of Economic Literature, 37*(4), 1615-1660.

Alesina, A., & Perotti, R. (1996). Income distribution, political instability, and investment. *European Economic Review, 40*(6), 1203-1228.

Alesina, A., & Rodrik, D. (1994). Distributive Politics and Economic Growth. *Quarterly Journal of Economics 109*(2), 465-490.

Amadou, D. I. (2010). XTDOLSHM: Stata module to perform panel data cointegration. *Statistical Software Components S457173, Boston College Department of Economics*.

Andrade, J. S., Duarte, A., & Simões, M. (2011). Inequality and Growth in Portugal: A time series analysis. *GEMF Working Papers, 11/2011*.
Arbia, G., Dominicis, L. d., & Piras, G. (2005). Regional Growth and Regional Inequality in EU and Transition Countries: a Spatial Econometric Approach. *ERSA conference papers, ersa05p168*.
Balisacan, A. M., & Fuwa, N. (2003). Growth, inequality and politics revisited: a developing-country case. *Economics Letters, 79*, 53-58.
Baltagi, B. (2005). *Econometric Analysis of Panel Data* (3rd ed.). Chichester: John Wiley & Sons.
Banerjee, A. V., & Duflo, E. (2003). Inequality and Growth: What Can the Data Say? *Journal of Economic Growth, 8*(3), 267-299.
Barro, R. J. (2000). Inequality and growth in a panel of countries. *Journal of Economic Growth, 5*(1), 87-120.
Benabou, R. (1996). Inequality and economic growth. In B. Bernanke & J. Rotemberg (Eds.), *NBER Macroeconomics Annual* (pp. 11-76). Cambridge, Massachusetts: MIT Press.
Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development: Evidence from aggregate cross-country data. *Journal of Monetary Economics, 34*(2), 143-173.
Benhabib, J., & Spiegel, M. (2005). Human Capital and Technology Diffusion. In P. Aghion & S. Durlauf (Eds.), *Handbook of Economic Growth* (Vol. 1A, pp. Chapter 13, 935-966). Amsterdam: North Holland.
Bertola, G. (1993). Factor Shares and Savings in Endogenous Growth. *American Economic Review 83*(5), 1184-1198.
Bertola, G., Foellmi, R., & Zweimuller, J. (2006). *Income distribution in macroeconomic models*. Princeton: Princeton University Press.
Bleaney, M., & Nishiyama, A. (2004). Income Inequality and Growth: Does the Relationship Vary with the Income Level? *Economics Letters, 84*(3), 349-355.
Cardoso, C., & Pentecost, E. J. (2011). Regional Growth and Convergence: The Role of Human Capital in the Portuguese Regions. *Loughborough University DEPARTMENT OF ECONOMICS DISCUSSION PAPER SERIES, 2011 - 03*.
Chen, B. L. (2003). An Inverted-U Relationship between Inequality and Long-Run Growth. *Economics Letters, 78*(2), 205-212.
Clarke, G. R. G. (1995). More evidence on income distribution and growth. *Journal of Development Economics, 47*, 403-427.
Deininger, K., & Squire, L. (1996). A new data set measuring income inequality. *World Bank Economic Review, 10*(3), 565-591.
Deininger, K., & Squire, L. (1998). New ways of looking at old issues: inequality and growth. *Journal of Development Economics, 57*(2), 259-287.
Dominicis, L. D., Florax, R. J. G. M., & De Groot, H. L. F. (2008). A META-ANALYSIS ON THE RELATIONSHIP BETWEEN INCOME INEQUALITY AND ECONOMIC GROWTH. *Scottish Journal of Political Economy, 55*(5), 654–682.
Duarte, A., & Simões, M. (2011). Inequality and growth: relevant links for the Portuguese economy. In M. Radović-Marković, S. Redžepagić, J. S. Andrade & P. Teixeira (Eds.), *Serbia and the European Union: economic lessons from the new member states* (pp. 167-184). Belgrade: Institute of Economic Sciences.
Duarte, A., & Simões, M. (Forthcoming). Desigualdade e crescimento económico nas regiões portuguesas, 1995-2007Livro de Homenagem ao Doutor Aníbal de Almeida. Faculdade de Direito da Universidade de Coimbra.

Ehrhart, C. (2009). The effects of inequality on growth: a survey of the theoretical and empirical literature *ECINEQ Working Paper Series, ECINEQ 2009-107*.
Ezcurra, R. (2007). Is Income Inequality Harmful for Regional Growth? Evidence from the European Union. *Urban Studies 44*(10), 1953–1971.
Fallah, B. N., & Partridge, M. (2007). The elusive inequality-economic growth relationship: are there differences between cities and the countryside? *Annals of Regional Science, 41*, 375–400.
Fidalgo, J. G., Simões, M., & Duarte, A. (2010). Mind the Gap: Education Inequality at the Regional Level in Portugal, 1986-2005. *Notas Económicas, 32*, 22-43.
Fields, G. S. (2001). *Distribution and Development. A new look at the developing world*. Cambridge, Massachusetts: The MIT Press.
Forbes, K. (2000). A reassessment of the relationship between inequality and growth. *American Economic Review, 90*(4), 869-887.
Frank, M. W. (2009). Income Inequality, Human Capital, and Income Growth: Evidence from a State-Level VAR Analysis. *Atlantic Economic Journal, 37*, 173–185.
Galor, O., & Tsiddon, D. (1994). Human capital distribution, technological progress, and economic growth. *CEPR working paper no., 971*.
Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. *Review of Economic Studies, 60*, 35-52.
García-Peñalosa, C. (2008). Inequality and Growth: Goal Conflict or Necessary Prerequisite? *Proceedings of OeNB Workshops, Dimensions of Inequality in the EU, 16*.
Hadri, K. (2000). Testing for Stationarity in Heterogeneous Panel Data. *Econometrics Journal, 3*(2), 148-161.
Harris, R. D. F., & Tzavalis, E. (1999). Inference for Unit Roots in Dynamic Panels Where the Time Dimension Is Fixed. *Journal of Econometrics, 91*(2), 201-226.
Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics, 115*(1), 53-74.
Kao, C., & Chiang, M.-H. (2001). On the estimation and inference of a cointegrated regression in panel data. In B. H. Baltagi, T. B. Fomby & R. C. Hill (Eds.), *Nonstationary Panels, Panel Cointegration, and Dynamic Panels (Advances in Econometrics, Volume 15)* (pp. 179-222). Amsterdam: Emerald Group Publishing Limited.
Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics, 54*(1-3), 159-178.
Levin, A., & Lin, C.-F. (1992). Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. *Department of Economics, UC San Diego, University of California at San Diego, Economics Working Paper Series*.
Levin, A., & Lin, C.-F. (1993). Unit Root Tests in Panel Data: New Results. *Department of Economics, UC San Diego, University of California at San Diego, Economics Working Paper Series*.
Levine, R., & Renelt. (1992). A sensitivity analysis of cross-country growth regressions. *American Economic Review, 82*(4), 942-963.
Malinen, T. (2012). Estimating the long-run relationship between income inequality and economic development *Empirical Economics, 42*(1), 209-233.
Mankiw, N. G., Romer, D., & Weil, D. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics, 107*(2), 407-437.

Mark, N. C., & Sul, D. (2003). Cointegration Vector Estimation by Panel DOLS and Long-run Money Demand. *Oxford Bulletin of Economics and Statistics, 65*(5), 655-680.

Martins, N., & Barradas, S. (2009). Convergência Económica das Regiões Portuguesas, 1995-2006. *Documento de Trabalho DPP, 2*.

Panizza, U. (2002). Income Inequality and Economic Growth: Evidence from American Data. *Journal of Economic Growth, 7*(1), 25-41.

Partridge, M. (2005). Does income distribution affect U.S. state economic growth? *Journal of Regional Science, 45*(2), 363–394.

Partridge, M. D. (1997). Is inequality harmful for growth? Comment. *American Economic Review, 87*(5), 1019-1032.

Perotti, R. (1996). Democracy, income distribution and growth: What the data say. *Journal of Economic Growth, 1*, 149-187.

Persson, T., & Tabellini, G. (1994). Is Inequality Harmful to Growth? . *American Economic Review, 84*(3), 600-621.

Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence. *Journal of Applied Econometrics, 22*(2), 265-312.

Quah, D. (1994). Exploiting Cross Sectioniation for Unit Root Inference in Dynamic Data. *Economic letters, 44*, 9-19.

Quah, D. (1996). Empirics for Eonomic Growth and Convergence. *European Economic Review, 40*, 1353-1375.

Rodríguez-Pose, A., & Tselios, V. (2010). Inequalities in income and education and regional economic growth in western Europe. *Annals of Regional Science, 44*, 349-375.

Saikkonen, P. (1991). Asymptotically Efficient Estimation of Cointegration Regressions. *Econometric Theory, 7*(1), 1-21.

Sala-i-Martin, X. (1997). I just run two million regressions. *American Economic Review, 87*(2), 178-183.

Sianesi, B., & van Reenen, J. (2003). The Returns to Education: Macroeconomics. *Journal of Economic Surveys, 17*(2), 57-200.

Voitchovsky, S. (2005). Does the profile of income inequality matter for economic growth? Distinguishing between the effects of inequality in different parts of the income distribution. *Journal of Economic Growth, 10*, 273-296.

Xu, K. (2004). How Has the Literature on Gini's Index Evolved in the Past 80 Years? *mimeo, Department of Economics, Dalhousie University*

Table 1: IPS panel unit root test results

	Demean		Trend			Demean		Trend	
	T	Z	t	Z		t	Z	t	Z
ly	-1.38	0.60	-2.03	-2.37***	***dly***	-3.49***	-7.55***	-3.21***	-6.61***
lgini	-2,30***	-3,82***	-3.03***	-6.51***	***dlgini***	-4.32***	-9.08***	-4.45***	-9.40***
lr1050	-2.41***	-4.48***	-2.79***	-5.62***	***dlr1050***	-4.07***	-8.69***	-4.17***	-8.93***
lr9050	-2.67***	-5.43***	-2.61***	-5.54***	***dlr9050***	-4.31***	-9.14***	-3.89***	-8.61***
lh	-1.15	2.01	-1.57	-0.76	***dlh***	-3.54***	-7.93***	-4.30***	-9.86***
lasf	-1.54	0.32	-0.84	4.95	***dlasf***	-3,89***	-8,12***	-2,71***	-4,73***
e_Agr	-1.19	1.47	-1.62	-1.35*	***de_Agr***	-2,72***	-5,86***	-2,82***	-6,42***
e_Man	-1.30	1.02	-2.01	-2.74***	***de_Man***	-3,71***	-8,20***	-3,84***	-8,62***
e_Ser	-1.25	1.48	-2.22	-4.00***	***de_Ser***	-3,43***	-7,77***	-3,46***	-7,85***
lh	-1.00	3.24	-2.04	-2.74***	***dlh***	-3,86***	-8,28***	-4,21***	-8,98***
lhs	-0.71	5.26	-1.43	1.68	***dlhs***	-4,09***	-8,92***	-3,94***	-8,78***
lhh	-1.62	-0.12	-3.10***	-6.85***	***dlhh***	-4,60***	-9,41***	-4,75***	-9,84***

Notes: (***), (**) and (*) indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2: HT panel unit root test results

	Demean	Trend		Demean	Trend
	Z	Z		Z	Z
ly	0.30	0.64	***dly***	-22,28***	-7,46***
lgini	-7,69***	-26,97***	***dlgini***	-26,57***	-14,40***
lr1050	-10.60***	-9.28***	***dlr1050***	-26.82***	-14.76***
lr9050	-17.78***	-12.64***	***dlr9050***	-34.40***	-20.01***
lh	0,44	0.56	***dlh***	-20,57***	-10.55***
lasf	2.15	-0.77	***dlasf***	-24,97***	-10,11***
e_Agr	2.80	0.98	***de_Agr***	-15,84***	-3,52***
e_Man	1.63	0.28	***de_Man***	-21,81***	-8,82***
e_Ser	1.50	-1.50*	***de_Ser***	-20,13***	-8,33***
lh	1.61	-2.40***	***dlh***	-22,59***	-11,45***
lhs	3.93	-0.21	***dlhs***	-22,97***	-8,56***
lhh	-1.66**	-8.83***	***dlhh***	-27,59***	-14,38***

Notes: (***), (**) and (*) indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3: CADF panel unit root test results

	Demean	Trend		Demean	Trend
	t	t		t	t
ly	-2.02	-3,00***	***dly***	-3,03***	-3,21***
lgini	-2.25**	-2.03	***dlgini***	-2,21**	-2.4
lr1050	-2.13*	-2.24	***dlr1050***	-2.49***	-2.46
lr9050	-2.40***	-2.34	***dlr9050***	-2.36***	-2.52
lh	-1.90	-1.78	***dlh***	-2,14*	-2.22
lasf	-1.04	-2.42	***dlasf***	-2,33**	-2.19
e_Agr	-1.59	-2.46	***de_Agr***	-1.95	-2.26
e_Man	-1.49	-2.56	***de_Man***	-2,66***	-2.52
e_Ser	-2.04	-2,99***	***de_Ser***	-2,87***	-2,73**
lh	-1.29	-0.98	***dlh***	-1.45	-2.21
lhs	-1.00	-1.81	***dlhs***	-1.87	-2.16
lhh	-2,10*	-1.93	***dlhh***	-2,23**	-2.43

Notes: (***), (**) and (*) indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: Hadri panel unit root test results

	Demean	Trend		Demean	Trend
	Z	Z		Z	Z
ly	14,99***	10,90***	***dly***	1,31*	6,17***
lgini	5,84***	4,39***	***dlgini***	-1.79	1,39****
lr1050	8.81***	4.05***	***dlr1050***	0.01	3.33***
lr9050	4.16***	3.63***	***dlr9050***	-2.27	2.47***
lh	9,87***	9,57***	***dlh***	2.57***	2.17**
lasf	16,90***	10,40***	***dlasf***	-0.48	6,59***
e_Agr	17,47***	8,32***	***de_Agr***	-0.28	1,84**
e_Man	17,24***	11,45***	***de_Man***	-0.24	4,67***
e_Ser	15,84***	8,78***	***de_Ser***	-0.61	2,46***
lh	13,61***	9,12***	***dlh***	2,73***	3,94***
lhs	16,67***	11,36***	***dlhs***	2,74***	2,73***
lhh	17,11***	5,08***	***dlhh***	0.75	2,72***

Notes: (***), (**) and (*) indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: DOLS long-run estimates with the Gini index as the inequality measure

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
lh	1.215	0.728	0.340	1.110	0.510	0.501	0.480	0.784										
	(19.06)	(16.77)	(5.81)	(16.20)	(12.17)	(8.09)	(7.04)	(11.76)										
lhs									0.885	0.554	0.628	0.956	0.516	0.996	0.449	0.887	0.433	0.546
									(24.58)	(13.85)	(6.47)	(10.11)	(4.75)	(9.52)	(4.33)	(8.57)	(4.25)	(5.44)
lhh													0.185	0.340	0.200	0.351	0.232	0.298
													(4.96)	(5.54)	(5.45)	(6.24)	(4.19)	(5.52)
years	-0.298			-0.027		-0.012	-0.010	-0.020			-0.014	-0.028		-0.055		-0.055	-0.029	-0.042
	(10.66)			(10.06)		(4.43)	(3.17)	(6.78)			(3.27)	(7.47)		(8.64)		(9.00)	(4.67)	(7.22)
lgini	-0.192	-0.167	-0.202	-0.740	0.141	-0.058	-0.201	0.129	-0.098	0.156	-0.126	0.178	-0.180	-0.123	-0.169	-0.113	-0.165	0.087
	(5.31)	(4.22)	(5.00)	(4.93)	(3.92)	(1.94)	(5.95)	(3.97)	(2.97)	(4.97)	(3.93)	(5.75)	(4.86)	(3.52)	(5.05)	(3.53)	(5.20)	(2.84)
lasf		-0.036	-0.018	-0.034	-0.017	-0.014	-0.018	-0.017	-0.031	-0.017	-0.019	-0.017			-0.032	-0.030	-0.023	-0.019
		(11.18	(5.74	(12.15	(5.98)	(5.79)	(6.39)	(6.31)	(13.76)	(7.95)	(7.72)	(7.18)			(12.90)	(11.99)	(9.20)	(7.93)
e_Man						0.499												
						(1.81)												
e_Ser			1.262			1.395	1.238				1.051						0.836	
			(3.60)			(4.61)	(3.80				(3.40						(2.75)	
e_Agr					-1.114			-1.076		-0.982		-0.872						-0.794
					(4.18)			(4.12)		(3.88)		(3.53)						(3.23)
Wald(k)	493.88	817.88	310.09	1013.62	536.86	411.68	399.22	535.24	953.03	614.18	208.18	302.03	708.44	321.65	1235.72	465.61	366.88	325.67

Notes: t-statistics values are reported in parentheses. All coefficients are statistically significant at least at the 10% levels. The Wald(k) is a $X^2(k)$ statistics for the null of the regression coefficients. The DOLS methodology was applied in panel cointegration estimations using the procedure xtdolshm for STATA 11.0 (see Amadou (2010)) based on the GAUSS code from Kao, C. and Chiang, M. H.: 2002, "Nonstationary Panel Time Series Using NPT 1.3 A User Guide", Center for Policy Research, Syracuse University. Leads & lags=1.

Table 6: DOLS long-run estimates with the ratio 10/50 as the inequality measure

	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
lh	0.736 (17.66)	1.206 (17.37)	0.628 (14.99)	0.325 (5.64)	0.452 (11.05)	1.151 (18.65)	0.545 (7.93)	0.636 (9.49)												
lhs									0.869 (25.04)	1.447 (14.60)	0.374 (7.60)	0.535 (13.82)	0.675 (6.93)	0.860 (9.00)	0.462 (4.22)	0.940 (8.90)	0.420 (4.05)	0.857 (8.23)	0.408 (4.49)	0.460 (4.50)
lhh															0.189 5.09	0.388 6.24	0.199 5.49	0.391 6.85	0.260 5.33	0.273 4.88
years		-0.032 (12.07)				-0.039 (17.04)	-0.015 (4.83)	-0.012 (4.34)		-0.041 (10.48)			-0.018 (4.36)	-0.021 (5.67)		-0.062 (9.66)		-0.061 (9.84)	-0.034 (6.25)	-0.038 (5.96)
lr1050	0.381 (4.59)	0.474 (6.57)	0.760 (10.22)	0.408 (4.85)	-0.606 (7.84)	0.901 (14.57)	0.447 (6.27)	-0.530 (7.74)	0.282 (4.05)	0.314 (4.59)	0.350 (5.05)	-0.558 (8.34)	0.355 (5.27)	-0.423 (6.46)	0.473 (6.23)	0.615 (8.47)	0.408 (5.84)	0.547 (8.01)	0.117 (2.01)	0.506 (7.55)
lasf	-0.034 (10.77)	-0.031 (10.91)	-0.032 (11.39)	-0.017 (5.27)	-0.018 (6.14)	-0.027 (11.10)	-0.015 (5.47)	-0.017 (6.53)	-0.030 (12.72)	-0.026 (10.09)	-0.018 (7.25)	-0.018 (8.11)	-0.017 (6.53)	-0.018 (7.33)			-0.029 (11.65)	-0.025 (9.90)	-0.018 (8.12)	-0.020 (7.70)
e_Man			-0.519 (1.68)			-0.576 (2.26													0.495 (1.95	
e_Ser				1.260 (3.70)			1.224 (3.74)				1.140 (3.88)		1.023 (3.30)						0.959 (3.36)	0.761 (2.49)
e_Agr					-1.314 (4.93)			-1.259 (4.80)				-1.159 (4.55)		-0.993 (7.33)						
Wald(k)	839.02	929.71	904.76	303.67	562.37	1051.94	337.73	610.36	930.54	376.57	386.29	643.23	221.13	364.06	725.30	328.54	1192.18	383.69	335.73	289.50

Notes: t-statistics values are reported in parentheses. All coefficients are statistically significant at least at the 10% levels. The Wald(k) is a $X^2(k)$ statistics for the null of the regression coefficients. The DOLS methodology was applied in panel cointegration estimations using the procedure xtdolshm for STATA 11.0 (see Amadou (2010)) based on the GAUSS code from Kao, C. and Chiang, M. H.: 2002, "Nonstationary Panel Time Series Using NPT 1.3 A User Guide", Center for Policy Research, Syracuse University. Leads & lags=1.

Table 7: DOLS long-run estimates with the ratio 90/50 as the inequality measure

	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56
lh	0.679	1.052	0.291	0.515	0.455	0.794												
		(15.37)	(5.54)	(12.44)	(7.41)	(12.05)												
lhs							1.486	0.368	0.577	0.699	0.721	1.041	1.076	0.959	0.210	1.018	0.490	0.619
							(15.00)	(8.19)	(14.67)	(8.17)	(7.38)	(11.00)	(10.29)	(9.17)	(2.08)	(11.22)	(5.40)	(6.14)
lhh													0.313	0.327	0.170	0.366	0.246	0.285
													(5.11	(5.77	(4.90	(7.56	(5.08	(5.26
years		-0.027			-0.012	-0.020	-0.043			-0.021	-0.019	-0.032	-0.058	-0.058		-0.064	-0.036	-0.045
		(9.99)			(4.44)	(7.21)	(11.07)			(5.74)	(4.65)	(8.57)	(9.04)	(9.34)		(12.14)	(6.66)	(7.63)
lr9050	-0.088	-0.076	0.131	0.208	0.131	0.207	0.169	0.181	0.260	0.239	0.089	0.335	0.068	0.064	0.180	0.162	0.202	0.239
	(1.97)	(1.98)	(3.18)	(5.07)	(3.93)	(5.71)	(4.57)	(5.28)	(7.32)	(7.54)	(2.43)	(9.61)	(1.74)	(1.76)	(5.04)	(5.18)	(6.64)	(6.88)
lasf	-0.037	-0.035	-0.015	-0.017	-0.014	-0.016	-0.029	-0.016	-0.016	-0.015	-0.021	-0.016		-0.030	-0.017	-0.027	-0.018	-0.018
	(11.47)	(12.61)	(5.24)	(5.82)	(5.88)	(6.18)	(11.22)	(6.99)	(7.54)	(6.65)	(8.09)	(6.62)		(11.82)	(7.27)	(12.34)	(8.08)	(7.35)
e_Man			0.630		0.626			0.631		0.620						0.408	0.696	
			(1.92)		(2.31)			(2.33)		(2.4)						(1.74)	(2.77)	
e_Ser			1.486		1.452			1.358		1.215	0.982						1.023	
			(4.57)		(4.80)			(4.53)		(4.20)	(3.13)						(3.57)	
e_Agr				-1.109		-1.076			-0.983			-0.872			-0.973			-0.821
				(4.16)		(4.17)			(3.89)			(3.54)			(3.86)			(3.34)
Wald(k)	807.82	979.86	338.65	534.49	394.19	525.38	416.29	493.77	657.87	315.01	267.67	352.21	315.48	431.04	849.21	592.11	412.20	339.11

Notes: t-statistics values are reported in parentheses. All coefficients are statistically significant at least at the 10% levels. The Wald(k) is a $X^2(k)$ statistics for the null of the regression coefficients. The DOLS methodology was applied in panel cointegration estimations using the procedure xtdolshm for STATA 11.0 (see Amadou (2010)) based on the GAUSS code from Kao, C. and Chiang, M. H.: 2002, "Nonstationary Panel Time Series Using NPT 1.3 A User Guide", Center for Policy Research, Syracuse University. Leads & lags=1.

Table 8: DOLS long-run estimates with the simultaneous influence of the ratios 10/50 and 90/50

	57	**58**	**59**	**60**	**61**	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**
lh	1.322 (20.63)	1.206 (17.85)	0.302 (5.32)	0.432 (10.49)	0.479 (7.82)	0.539 (8.01)	0.629 (9.61)																
lhs								0.900 (23.33)	1.659 (17.23)	0.870 (24.85)	1.577 (16.31)	0.375 (7.73)	0.538 (13.86)	0.727 (8.51)	0.803 (8.41)	0.985 (10.54)	0.480 (4.49)	1.072 (10.36)	0.437 (4.30)	0.983 (9.63)	0.207 (2.09)	0.522 (5.77)	0.580 (5.77)
lhh																	0.179 (4.90)	0.372 (6.08)	0.191 (5.32)	0.376 (6.71)	0.155 (4.54)	0.256 (5.25)	0.266 (4.82)
years	-0.037 (13.32)	-0.033 (12.52)			-0.013 (5.01)	-0.016 (5.40)	-0.013 (4.76)		-0.051 (14.17)		-0.050 (13.00)			-0.023 (6.36)	-0.026 (6.27)	-0.029 (7.85)		-0.069 (10.97)		-0.068 (11.13)		-0.040 (7.35)	-0.044 (7.07)
lr1050	0.635 (8.48)	0.525 (7.38)	0.484 (5.75)	-0.547 (7.02)	0.111 (1.79)	0.541 (7.67)	-0.457 (6.75)	0.454 (5.93)	0.643 (8.90)	0.376 (5.41)	0.564 (2.34)	0.464 (6.69)	-0.453 (6.79)	0.138 (2.33)	0.542 (8.10)	-0.202 (3.10)	0.520 (6.84)	0.824 (11.33)	0.446 (6.43)	0.743 (10.95)	-0.367 (5.51)	0.279 (4.70)	0.673 (10.06)
lr9050	0.096 (2.38)	0.080 (2.09)	0.122 (2.66)	0.118 (2.56)	0.144 (4.25)	0.143 (3.73)	0.133 (3.65)	0.155 (3.72)	0.387 (3.83)	0.140 (3.75)	0.361 (9.88)	0.167 (4.42)	0.179 (5.04)	0.259 (8.07)	0.271 (7.44)	0.292 (8.38)	0.084 (2.04	0.323 (8.23)	0.066 (1.75)	0.296 (8.14)	0.120 (3.36)	0.242 (7.60)	0.248 (6.86)
lasf		-0.031 (11.13	-0.017 (5.27)	-0.018 (6.00)	-0.014 (5.68)	-0.015 (5.49)	-0.017 (6.50)			-0.029 (12.68)	-0.024 (9.41	-0.018 (7.14)	-0.017 (7.74)	-0.014 (6.35)	-0.016 (6.17)	-0.016 (6.76)			-0.029 (11.69)	-0.024 (9.37)	-0.017 (7.38)	-0.017 (7.68)	-0.019 (7.36)
e_Man					0.542 (1.99)									0.510 (2.01)								0.498 (1.97)	
e_Ser			1.271 (3.69		1.423 (4.71)	1.234 (3.81)						1.141 (3.88)		1.169 (4.06)	0.978 (3.19)							0.930 (3.26)	0.727 (2.40)
e_Agr				-1.333 5.02			-1.275 (4.98						-1.180 (4.71)			-0.966 (3.95)					-1.135 (4.55)		
Wald(k)	531.70	966.30	321.70	535.24	385.15	362.32	580.10	662.38	582.05	1021.39	537.09	472.00	677.13	308.39	323.19	364.87	784.79	531.82	1257.97	513.45	854.70	395.73	385.03

Notes: t-statistics values are reported in parentheses. All coefficients are statistically significant at least at the 10% levels. The Wald(k) is a $X^2(k)$ statistics for the null of the regression coefficients. The DOLS methodology was applied in panel cointegration estimations using the procedure xtdolshm for STATA 11.0 (see Amadou (2010)) based on the GAUSS code from Kao, C. and Chiang, M. H.: 2002, "Nonstationary Panel Time Series Using NPT 1.3 A User Guide", Center for Policy Research, Syracuse University. Leads & lags=1.