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Education and income inequality in the regions of the European Union

by

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Abstract

This paper provides an empirical study of the determinants of income inequality across regions of the EU. Using the European Community Household Panel dataset for 102 regions over the period 1995-2000, it analyses how microeconomic changes in human capital distribution affect income inequality. Human capital distribution is measured in terms of both educational attainment as well as educational inequality. Income and educational inequalities are calculated by a generalised entropy index (Theil index). Different static and dynamic panel data analyses are conducted in order to reduce measurement error on inequalities and minimise potential problems of omitted-variable bias. Taking into account the specification tests applied to the estimated models, the regression results reveal that, while the relationship between income inequality and income per capita is positive, the long-run relationship between income inequality and educational attainment is not statistically significant. This paper also agrees with the current belief that human capital inequality has a positive relationship with income inequality. Across European regions high levels of inequality in educational attainment are associated with higher income inequality. This may be interpreted as the responsiveness of the EU labour market to differences in qualifications and skills. Other results indicate that the average age of respondents and inactivity are sensitive to the specification model, while economic activity and urbanisation are negatively associated to income inequality. Furthermore, the relationship between unemployment and income inequality is positive. Female participation in the labour force is negatively associated with inequality and explains a major part of the variation in inequality. Finally, as expected, income inequality is lower in democratic welfare states, in Protestant areas, and in regions with Nordic family structures (i.e. Swedish and Danish regions).

Keywords: Income inequality, educational attainment, educational inequality, regions, Europe

1. Introduction

It is often claimed that greater educational attainment makes societies more egalitarian, and income and educational inequalities are perfectly correlated (Checchi, 2000). But, in spite of these claims, the influence of education on inequalities is still a long way from being perfectly understood, especially at a regional level. This paper addresses the questions of the supposed negative relationship between educational attainment and income inequality and of the positive correlation between inequality in education and in income for the regions of the EU. Our methodology is based on the estimation of various specification models (both static and dynamic) in order to assess the sensitivity of the relationships.

This aim of the paper is to analyse how microeconomic changes in human capital distribution affect income inequality. Human capital is generally a multidimensional concept and has been defined by the OECD (1998, p.9) as '*the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity'*. In this paper human capital distribution is measured both in terms of the average education of the population and the inequality in educational attainment. By analysing the microeconomic processes underpinning the relationship between individual educational endowments and income inequality, we also expect to draw greater light on whether government education policies contribute to a more equal income distribution and whether EU labour market is responsive to differences in qualifications, knowledge and skills.

The paper is organised in five additional sections. The next section reviews the existing debate over the determinants of income inequality, putting greater emphasis on the relationship between income and human capital distribution. The empirical regression model and the relevant static and dynamic estimation methods are discussed in Section 3. Section 4 describes the data and the construction of variables. Section 5 reports and discusses the regression results and finally Section 6 concludes with policy recommendations and some suggestions for further research.

2. Theoretical considerations

There is a vast literature on the determinants of income inequality. It is therefore not the aim of this section to review this vast array of sources, but simply to focus on how the impact of income per capita, as well as of average and inequality levels of education on income inequality is perceived by the literature. In order to do that, we will first review the link between income and inequality, followed by the analysis of the impact of educational attainment and inequality on income inequality. We will also consider the dynamic structure of inequalities.

Changes in the distribution of income take place at a very slow pace. There are several reasons for this. First, people are often reluctant to change jobs for psychological and institutional reasons (Gujarati, 1995). Additionally, income levels are often perpetuated from one generation to another by means of inheritance, cultural background and, more generally, characteristics of the community (Bourguignon and Morrisson, 1990; Cooper *et al*., 1994; Durlauf, 1996; Checchi, 2000). This allows for intergenerational stability in income, denoting the existence of a positive autocorrelation in inequalities. Cooper (1998), for instance, has pointed out that families from poor communities or wealthy communities tend to exhibit higher intergenerational income stability than families living in middle income communities. Hence, it is often the case that a proportion of the population remains trapped at low and high levels of income for more than one generation. Income persistence is often viewed (e.g. Lane, 1971) as an essential characteristic of rewarding achievement and, particularly, of ensuring that the most suitable persons are allocated the most suitable roles. The presence of inequalities in income provides an additional incentive to achievement and innovation which are an integral part of modern society. Some degree of inequality is generally perceived as a necessary constituent of a healthily functioning economy (Champernowne and Cowell, 1998, p.14). The question is whether the persistence of inequality has an impact on economic performance. Do unequal societies perform better than more equal ones?

This relationship has been most famously addressed by Kuznets (1955) in his now famous Kuznets' curve (Kuznets, 1955), which was later formalised by Robinson (1976), Knight (1976) and Fields (1979). Income levels have an inverted U-curve effect on income inequality. Income inequality increases as nations begin to industrialise and then declines at the later stages of industrialisation. Two fundamental factors which shape the inverted U-curve are the level of industrialisation (or the degree of integration) and labour migration. More specifically, in the early stages of development, the highest portion of the labour force is engaged in agriculture. As industrialisation, or more generally speaking, as economic, social and political integration proceeds, workers move from the larger agricultural sector to the smaller industrial one where wages are usually higher. This migration boosts initially even more income inequality. This in turn implies that income distribution becomes more unequal as income increases. However, according to neoclassical economic theory, as the agricultural sector shrinks and industry grows, further movement from the agricultural to the industrial sector increases agricultural wages reducing income inequality. Therefore, development is inegalitarian in the early stages of development and becomes egalitarian at the later stages.

Despite the significant amount of the research that has tried to test whether the Kuznets curve works at the national level, the results are ambiguous (e.g. Ahluwalia, 1976; Papanek and Kyn, 1986; Anand and Kanbur, 1993; Bourguignon and Morrisson, 1998; Checchi, 2000; Motonishi, 2003). Ahluwalia (1976), for instance, finds for a cross-section of counties evidence to support the inverted U-curve, while Anand and Kanbur (1993), in contrast, report that the Kuznets curve is not inverse at all. Overall the literature seems unable to provide conclusive empirical results on the relationship between income inequality and income per capita, because social structures, such as historical heritage, religion, ethnic composition and cultural traditions, across countries evolve differently (Checchi, 2000). In this paper, we do not expect to test the validity of the Kuznets curve, because firstly, the majority of the relevant empirical studies are based not only on European but also on less economically advanced countries (i.e. African countries) and secondly, because these studies show that the declining segment of the Kuznets curve begins approximately from 1970 (Nielsen and Alderson, 1997). But we use Kuznets' theory in order to assume a linear association between income per capita and income inequality for developed countries over a relatively limited period of time. We thus expect that over the period 1995-2000 income per capita has a negative effect on income inequality.

The notion of education as a factor behind income differences also has a long history, going back to Adam Smith (Griliches, 1997). Stemming from the work of Schultz (1961, 1962), Becker (1962, 1964) and Mincer (1958a,b, 1974), income inequality is generally considered to be affected by educational attainment, which is sometimes called ‘skills deepening’ (Williamson 1991). Higher educational attainment is achieved through improvements in access to education (i.e. lower tuition fees, better education financing, improved vocational training), higher quality of education (i.e. better services of teachers, librarians and administrators) and greater investment in physical capital for education. Improving access to education, for example, is likely to raise the earning opportunity of the lowest strata, leading to lower earning inequality (Checchi, 2000). Furthermore, a widespread access to education allows for a more informed participation in the market economy, reduces the lobbying ability of the rich, while simultaneously increases the social and job opportunities of the poor, implying lower inequality. The recent studies of DeGregorio and Lee (1999), Eicher and García-Peñalosa (2001) and Heshmati (2004) illustrate that higher educational attainment contributes to make income distribution more equal.

According to Knight and Sabot (1983), the impact of educational attainment in income inequalities depends on the balance between the ‘composition’ and the ‘wage compression’ effect. Their suggestions are based on the assumption that greater inequality of educational attainment is translated into greater income inequality. Concerning the ‘composition’ effect, an increase in the levels of education of the population tends, at least initially, to increase income inequality. With respect to the ‘wage compression’ effect, education tends to decrease income inequality. Additionally, an increase in the educated labour supply should increase competition for positions requiring advanced educational credentials and thereby should reduce the income differential between the educated and uneducated people (Tinbergen, 1975; Lecaillon *et al.*, 1984).

A different perspective on the relationship between income and education is given by Spence’s (1973, 1974) signalling model. This model depicts that education has no direct effect on income distribution, because education acts as a ‘label’ or ‘signal’. More specifically, his model posits a situation in which the possibility of higher pay of more educated people has nothing to do with academic and vocational skills, because formal education is seen as an elaborate device for detecting and labelling those who have skills (Chambernowne and Cowell, 1998; Wolf, 2004). The education level is more related with innate ability and with psychological and personality traits, such as diligence, and these are what employers reward, rather than regarding education as a means of instilling or enhancing skills (Wolf, 2004). Nevertheless, education still works as a marker for achieving better jobs. To sum up, given the complexity of the relationship between education and income, it is difficult to predict a priori the sign and the significance of the relationship between educational attainment and income inequality.

Finally most theoretical analyses tend to report that income and human capital inequality are positively correlated (Glomm and Ravikumar, 1992; Saint-Paul and Verdier, 1993; Jacobs, 1985; Gallor and Tsiddon, 1997a; Chakravorty, 2003). More explicitly, Thorbecke and Charumilind (2002, p.1488) have pointed out that, with regard to the supply side of skilled labour education, a greater share of highly educated workers within a cohort may signal to the employers that those with less education have lower ability, and hence the latter's earnings may be reduced accordingly, which may also lead to larger wage inequality between high and low education workers. With respect to the demand side of skilled labour education, if the demand for unskilled labour is either contracting or growing at a slower rate than the demand for skilled labour, then earning inequalities will increase.

Two of the most salient empirical works that focus on the impact of human capital distribution in terms of average and inequality levels on income inequality are Becker and Chiswick (1966) and Park (1996). Both studies illustrate that a higher level of educational attainment of the labour force has an equalizing effect on income distribution and the larger the inequality of educational attainment, the greater the income inequality.

3. Econometric approach

As a means to test whether the above-reported findings hold in a European regional context, using microeconomic data, this paper estimates income inequality as a function of per capita income, educational attainment and educational inequality. We use different empirical specifications in order to assess the robustness of the econometric models and to examine the impact of adding control variables, such as age, unemployment, economic activity rate, labour force stock and urbanisation. The methodology incorporates variability both across regions and over time. It constitutes a pooled cross-sections analysis. Our emphasis is on the case where $N \to \infty$ with T fixed and on the one-way error component model, due to the limited number of observations. Different static and dynamic panel data analyses are conducted in order to reduce measurement error on inequalities and minimise potential problems of omitted-variable bias. Panel data also allow for greater degrees of freedom than with time-series or cross-regional data and improve the accuracy of parameter estimates (Hsiao, 2003; Baltagi, 2005). Thus in order to examine the impact of education on income inequality and to evaluate the robustness of the results, we not only experiment with a number of alternative static and dynamic specifications, but also include additional determinants to our equations.

3.1 Static econometric models

Our econometric analysis starts with a static panel data model of the form

$$y_{it} = \beta' x_{it} + \gamma' z_i + \nu_i + \varepsilon_{it} \qquad (1)$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...,6$)[1]. y_{it} is income inequality, x_{it} is a vector of explanatory variables (income per capita, educational attainment, educational inequality, age, labour force stock, total economic activity rate, unemployment, inactivity and female economic activity rate), z_i is the urbanisation ratio of a region, β and γ are coefficients, ν_i is an unobserved regional-specific effect (unobserved heterogeneity) and ε_{it} is the disturbance term with $E[\varepsilon_{it}] = 0$ and $Var[\varepsilon_{it}] = \sigma_\varepsilon^2$ (idiosyncratic error). The term $v_i + \varepsilon_{it}$ is the composite error.

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[1] $t = 1$ denotes 1995, …, $t = 6$ denotes 2000

We then consider the role of welfare state, religion and family structure on income inequality. These are explanatory variables, represented by dummies in the static panel data model. Our analysis takes on the following form:

$$y_{it} = \beta' x_{it} + \eta' d_{\lambda i} + \nu_i + \varepsilon_{it}, \qquad (2)$$

where η are coefficients and $d_{\lambda i}$ is a vector of dummy variables with λ denoting categories ($\lambda = 2,...,m$). If a qualitative variable has m categories, we introduce $m-1$ dummy variables (categories). Category d_{1i} is referred to as the base category. Comparisons are made with that category (Gujarati, 1995).

This static model is characterised by one source of persistence over time due to the presence of unobserved regional-specific effects. The presented static methods of panel estimation are pooled ordinary least squares (OLS), fixed effects (FEs) and random effects (REs). To evaluate which technique is optimal, it is necessary to consider the relationship between the regional-specific effects and the regressors, among others. First, the pooled OLS estimator assumes that the unobserved regional-specific effect is uncorrelated with the explanatory variables and each region is independent and identically distributed, ignoring the panel structure of the data and the information it provides (Johnston and DiNardo, 1997). The resulting bias in pooled OLS is caused from omitting a time-constant variable and is sometimes called heterogeneity bias (Wooldridge, 2003, p.439). Second, the FEs estimator (or within estimator) assumes that some or all of the regressors are correlated with the unobserved heterogeneity. Besides, the main reason for collecting panel data is to allow for the unobserved heterogeneity to be correlated with the explanatory variables (Wooldridge, 2003, p.440). FEs estimator is obtained by removing the unobserved regional characteristics which is a potential source of bias. More specifically, it is a pooled OLS estimator that is based on the time-demeaned variables. FEs estimator also requires that there be within-group variation in variables for at least some groups. We therefore introduce a year dummy variable with the urbanisation degree (time constant variable) in order to see whether the effect of urbanisation has changed over 1995-2000. Third, the REs estimator assumes that the regional-specific effects are uncorrelated with all the explanatory variables in all time periods. The provided efficient estimator of the REs model in this study is the generalised least squares (GLS) estimator. Both the FEs and the REs models deal with heterogeneity bias. The former treats the v_i as fixed effects to be estimated, while the latter treats the v_i as a random component of the error term.

Both FEs and REs estimators are based on the strict exogeneity assumption. Hence the vector of the explanatory variables (x_{it} and z_i) is strictly exogenous. It should be mentioned that the parameters from the static models are long-run parameters. The usual diagnostic tests are presented. Hausman's (1978) chi-squared statistic tests whether the GLS estimator is an appropriate alternative to the FEs estimator. Another critical diagnostic test is Breusch and Pagan's (1980) Lagrange multiplier (LM) statistic which is a test of the REs model against OLS model. LM test is a test for regional effects. Large values of LM statistic favour the REs model.

In the static models, we assume that the regression disturbances are homoskedastic with the same variance across time and regions. However, heteroskendasticity potentially causes problems for inferences based on least squares. Assuming homoskedastic disturbances in the FEs model, for example, might be a restrictive assumption for panels (Baltagi, 2005). Thus when heteroskedasticity is present, the consistent estimates are not efficient. If every ε_{it} has a different variance, the robust estimation of the FEs OLS covariance matrix is presented following the White estimator for unspecified heteroskedasticity (White, 1980). We also report the robust standard errors of each equation.

3.2 Dynamic econometric models

There are a variety of different techniques that can be used to estimate a dynamic model of the form:

$$y_{it} = \delta y_{i,t-1} + \beta' x_{it} + \zeta' x_{i,t-1} + \gamma' z_i + \nu_i + \varepsilon_{it} \qquad (3)$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 2,...,6$)[2]. y_{it} is income inequality, $y_{i,t-1}$ is the first lagged income inequality, x_{it} is a vector of explanatory variables, $x_{i,t-1}$ is a vector of first lagged explanatory variables, z_i is the urbanisation ratio of a region, δ, β, ζ and γ are coefficients, ν_i are the random effects (unobserved regional-specific effects) that are independent and identically distributed over the panels and ε_{it} is the disturbance term with $E[\varepsilon_{it}] = 0$ and $Var[\varepsilon_{it}] = \sigma_\varepsilon^2$ (idiosyncratic error). It is assumed that the ν_i and the ε_{it} are independent for each i over all t.

This dynamic model is characterised by two sources of persistence over time: autocorrelation due to the presence of a lagged dependent variable among the regressors and unobserved regional-specific effects (Baltagi, 2005). Pooled OLS, FEs and REs estimators are now biased and inconsistent, because econometric model contains a lagged endogenous variable (Baltagi, 2005).

The dynamic panel structure of our data is exploited by a generalised method of moments (GMM) estimation suggested by Arellano and Bond (1991) (Arellano-Bond estimation). The main idea behind GMM estimation is to establish population moment conditions and then use sample analogs of these moment conditions to compute parameter estimates (Greene, 2000; Wooldridge 2002; Baltagi, 2005). Arellano and Bond first transform the model to eliminate the regional-specific effect (ν_i). The observed urbanisation ratio (z_i) is eliminated as well. The first-differencing transformation is:

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + \beta'(x_{it} - x_{i,t-1}) + \zeta'(x_{i,t-1} - x_{i,t-2}) + (\varepsilon_{it} - \varepsilon_{i,t-1}), \tag{4}$$

where all variables are expressed as deviations from period means. Models in first differences usually face the problems arising from the non-stationarity of the data. The correlation between the explanatory variables and the error is handled by instrument variables (IVs). In Arellano-Bond estimations, the predetermined and endogenous variables in first differences are instrumented with suitable lags of their own levels, while the strictly exogenous regressors can enter the instrument matrix in first differences. For

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[2] $t = 2$ denotes 1996, …, $t = 6$ denotes 2000.

instance, for 1997 $(t = 3)$, $y_{i,1}$ is an instrument for $(y_{i,2} - y_{i,1})$ and not correlated with $(\varepsilon_{i3} - \varepsilon_{i2})$ as long as the ε_{it} themselves are not serially correlated; for 1998 $(t = 4)$, $y_{i,1}$ and $y_{i,2}$ are instruments for $(y_{i,3} - y_{i,2})$, and so on. This procedure is more efficient than the Anderson and Hsiao (1981, 1982) two stage least squares estimator which does not make use of all of the available moment conditions (Ahn and Schmidt, 1995). Anderson and Hsiao use $(y_{i,t-2} - y_{i,t-3})$ or $y_{i,t-2}$ only as an instrument for $y_{i,t-1} - y_{i,t-2}$. The Arellano-Bond structure provides a large number of IVs by GMM estimator. The Arellano-Bond framework, which is called 'difference GMM' (GMM-DIF), treats the dynamic model as a system of equations, one for each time period.

In our model, we assume that the explanatory variables might be:

a. strictly exogenous, if $E[x_{it}\varepsilon_{is}] = 0$ for all t and s,

b. predetermined, if $E[x_{it}\varepsilon_{is}] \neq 0$ for $s < t$, but $E[x_{it}\varepsilon_{is}] = 0$ for all $s \geq t$, and

c. endogenous, if $E[x_{it}\varepsilon_{is}] \neq 0$ for $s \leq t$, but $E[x_{it}\varepsilon_{is}] = 0$ for all $s > t$;

except for the average age of respondents which is definitely a strictly exogenous variable.

The GMM methodology is based on a set of diagnostics. First of all, it assumes that there is no second-order autocorrelation in the first-differenced idiosyncratic errors[3]. Additionally, Arellano and Bond (1991) developed Sargan's test (Sargan, 1958) of over-identifying restrictions. The Sargan test has an asymptotic chi-squared distribution in the case of homoskedastic error term only. Both the homoskedastic one-step and the robust one-step GMM estimators are presented. The two-step standard error model is not recommended, because it tends to be biased downward in small samples (Arellano and Bond, 1991; Blundell and Bond, 1998). It also should be mentioned that treating variables as predetermined or endogenous increases the size of the instrument matrix very

[3] The consistency of the GMM estimator relies upon the fact that $E[\Delta\varepsilon_{it}\Delta\varepsilon_{i,t-2}] = 0$ (Arellano and Bond, 1991, p.282).

quickly. This implies that GMM estimators with too many overidentifying restrictions may perform poorly in small samples (Kiviet, 1995)[4].

The dynamic model is also used in order to obtain short-run and long-run parameters. The short-run effect of an independent variable is the first year effect of a change in this variable, whereas the long-run effect is the effect obtained after full adjustment of income inequality. The short-run effect of the variable x is β and its long-run effect is $\beta + \gamma / 1 - \delta$. Long-run standard errors are calculating using the Delta method (Greene, 2000).

Broadly speaking, the advantage of dynamic over static models is that the former correct the inconsistentcy introduced by lagged endogenous variables and, also, permits a certain degree of endogeneity in the regressors.

4. Data and variables

The quantitative data used to estimate the econometric models come from the European Community Household Panel (ECHP) data survey conducted by the EU during the period 1994-2001 (wave2-wave8) and the Eurostat's Regio data set. During that period the surveys were conducted regularly at approximately one-year intervals. In these surveys individuals were interviewed about their socioeconomic status. Data stemming from the ECHP can be aggregated regionally at NUTS1 level for the EU15. Unfortunately there are no data available for the Netherlands. Finnish regions had to be dropped from the sample because of the discrepancies between the regional division included in the ECHP and those in the Regio databank, the source of the macroeconomic variables. The resulting database includes 102 NUTS I or II regions from 13 countries in the EU[5]. On average 116.574 individuals were surveyed, with a maximum of 124,759 in 1997 and a minimum of 105,079 in 2001.

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[4] cited in STATA manual (release 8): cross-sectional time-series, p.24.

[5] NUTS I data for Austria, Belgium, Denmark, France, Greece, Ireland, Italy, Luxembourg, Spain, Sweden. NUTS II data for Germany, Portugal, and the UK.

The variable '*Total net personal income (detailed, NC, total year prior to the survey)*' from the ECHP is used as the main source for the average income and the level of income inequalities. This variable is regionalised. Income per capita (IMN) is transformed for the same level of prices using the harmonised indices for consumer prices and then is divided by 1000. Income inequality $(IGE1)$ is calculated using the generalised Theil entropy index (Theil, 1967). This index considers a region's population of individuals $i \in \{1,2,...,N\}$ where each person is associated with a unique value of the measured income. The total net personal income is the sum of wages and salaries, income from self employment or farming, pensions, unemployment and redundancy benefits or any other social benefits or grants, and private income. Income inequality is defined as $IGE1 = \sum_{i=1}^{N} y_i \log(Ny_i)$, where y_i is income share that is individual i's total income as a proportion of total income for the entire regional population. This index varies from 0 for perfect equality to $\log N$ for perfect inequality.

The average and the inequality level of human capital are calculated using the microeconomic variable '*Highest level of general or higher education completed*' which also is extracted from the ECHP data set. Individuals are classified into three educational categories: recognised third level education completed, second stage of secondary education level completed, and less than second stage of secondary education level completed. These categories, which are mutually exclusive, allow for international comparisons, because they are defined by the International Standard Classification of Education.

The average level of human capital (or average education level completed) was first has been defined by Psacharopoulos and Arriagada (1986) and Ram (1990). It corresponds to the educational attainment (or educational achievement) level and is given by the index $EMN = \sum_{j=1}^{3} L_j S_j$, where L_j is the proportion of the respondents who belong in the j^{th} category and S_j denotes an assessment of each category. At the risk of some oversimplification, we assume $S_1 = 2$ for recognised third level education completed,

$S_2 = 1$ for second stage of secondary education level completed, and $S_3 = 0$ for less than second stage of secondary education level completed. This assessment is based upon two critical assumptions. The first one is that an increase in the level of education will add a constant quantity to educational attainment, whether undertaken by a primary or secondary student, and the second one is that acquisition of postgraduate degrees will not add any quality to educational attainment, because both graduate and postgraduate degrees belong to the same educational category.

Following the work of Fan *et al.* (2000), we calculate the inequalities in educational attainment using an education Theil index $(EGE1)$. This is defined as $EGE1 = \sum_{i=1}^{N} z_i \log(Nz_i)$, where z_i is human capital share, that is, individual i's higher education level completed as a proportion of total human capital for the entire regional population. As in the case for income inequality the index has a minimum value of 0 when the entire population is concentrated in a single educational category, and a maximum of $\log N$.

As a way of controlling for the impact of additional factors, we also examine the impact of additional quantitative time-variant variables on income inequality: the average age of people (AGE), the percentage of normally working (15+ hours/week) respondents $(LFSTOCK)$, the percentage of unemployed respondents $(UNEM)$ and the percentage of inactive respondents $(INACTIVE)$ within a region. The source of these variables is again the ECHP data set. Other controls include the economic activity rate of the population $(ECACRA)$ and female activity rate $(ECACRF)$ from the Eurostat's Regio data set. These are also time-variant variables. The urbanization ratio of a region $(URBANDPA)$ is constructed as the percentage of respondents who live in a densely populated area. Data for this variable are only available for 2000 and 2001, and not for all countries. We assume that the urbanization ratio from 1995 to 2001 remains constant. This variable, therefore, introduces observed time-invariant effects.

The transformed data set with mean, standard deviation and minimum and maximum value for each of the variable is reported in Table 4.1[6]. The descriptive statistics show that the dataset is unbalanced, which is amenable to estimation methods that manage potential heterogeneity bias. Table 4.1 also depicts that income inequality has decreased slightly between 1995 and 2000. Human capital inequalities followed a similar declining trend over the period of analysis.

Table 4.1: Summary Statistics

Variable	Dedinition	Year	Source	Obs	Mean	Std. Dev.	Min	Max
IGE1	Income inequality (Theil index)	1995	ECHP	94	0.42	0.16	0.18	0.83
		1996		102	0.38	0.17	0.11	0.79
		1997		102	0.38	0.16	0.14	0.79
		1998		102	0.38	0.15	0.11	0.72
		1999		102	0.37	0.15	0.12	0.72
		2000		102	0.36	0.14	0.11	0.74
		1995-00		604	0.38	0.15	0.11	0.83
IMN	Income per capita (/1000)	1995	ECHP	94	9.76	3.54	3.40	18.93
		1996		102	10.39	3.51	3.43	19.02
		1997		102	11.30	3.71	3.52	19.09
		1998		102	11.39	3.74	3.79	19.89
		1999		102	12.00	3.95	3.88	20.88
		2000		102	12.81	4.55	4.05	21.14
		1995-00		604	11.30	3.96	3.40	21.14
EMN	Average education level completed	1995	ECHP	94	0.66	0.24	0.12	1.17
		1996		94	0.66	0.24	0.12	1.15
		1997		102	0.69	0.24	0.12	1.13
		1998		102	0.83	0.30	0.18	1.28
		1999		102	0.83	0.32	0.18	1.34
		2000		102	0.80	0.27	0.19	1.23
		1995-00		596	0.75	0.28	0.12	1.34
EGE1	Inequality on education level completed (Theil index)	1995	ECHP	94	0.90	0.45	0.21	2.38
		1996		94	0.89	0.45	0.23	2.42
		1997		102	0.86	0.46	0.23	2.42
		1998		102	0.70	0.40	0.21	2.09
		1999		102	0.72	0.42	0.20	2.06
		2000		102	0.72	0.39	0.17	2.02
		1995-00		596	0.79	0.44	0.17	2.42
AGE	Average on age of respondents	1995	ECHP	94	45.19	2.29	39.76	51.39
		1996		94	44.90	1.93	41.64	50.80
		1997		102	45.17	1.86	42.05	51.61
		1998		102	45.48	1.83	42.40	51.12
		1999		102	45.68	1.79	40.69	51.06
		2000		102	45.96	1.86	42.32	51.35
		1995-00		596	45.40	1.95	39.76	51.61

[6] Appendix A.1 shows the descriptive statistics of the ECHP quantitative and qualitative variables.

LFSTOCK	Percentage of normally working (15+ hours/week) respondents (self-defined)	1995	ECHP	94	0.52	0.07	0.34	0.68
		1996		94	0.52	0.07	0.31	0.66
		1997		102	0.52	0.08	0.34	0.68
		1998		102	0.53	0.07	0.36	0.71
		1999		102	0.54	0.08	0.36	0.73
		2000		102	0.54	0.07	0.37	0.68
		1995-00		596	0.53	0.07	0.31	0.73
ECACRA	Economic acrivity rate of total population	1995	Eurostat	65	54.90	7.47	42.00	74.80
		1996		90	57.03	6.94	41.50	72.60
		1997		90	56.96	6.91	41.80	72.50
		1998		92	57.34	6.56	42.50	72.30
		1999		94	57.80	6.64	42.40	72.70
		2000		94	57.89	6.61	42.90	74.50
		1995-00		525	57.10	6.85	41.50	74.80
UNEM	Percentage of unemployed respondents (self-defined)	1995	ECHP	94	0.06	0.03	0.00	0.17
		1996		94	0.06	0.03	0.02	0.16
		1997		102	0.06	0.03	0.01	0.15
		1998		102	0.05	0.03	0.00	0.15
		1999		102	0.05	0.03	0.00	0.15
		2000		102	0.04	0.03	0.01	0.15
		1995-00		596	0.05	0.03	0.00	0.17
INACTIVE	Percentage of inactive respondents (self-defined)	1995	ECHP	94	0.42	0.06	0.29	0.55
		1996		94	0.43	0.06	0.31	0.56
		1997		102	0.42	0.06	0.29	0.57
		1998		102	0.42	0.06	0.29	0.56
		1999		102	0.42	0.06	0.27	0.57
		2000		102	0.42	0.06	0.30	0.55
		1995-00		596	0.42	0.06	0.27	0.57
ECACRF	Female economic activity rate	1995	Eurostat	65	44.78	10.82	24.00	72.20
		1996		90	47.45	9.69	23.40	70.50
		1997		90	47.52	9.42	23.70	71.20
		1998		92	47.99	8.96	25.10	69.70
		1999		94	48.87	9.13	26.20	71.30
		2000		94	49.15	9.14	26.70	72.90
		1995-00		525	47.79	9.52	23.40	72.90
URBANDPAV	Percentage of respondents who live in a densely populated area	1995	ECHP	63	0.61	0.24	0.11	1.00
		1996		63	0.61	0.24	0.11	1.00
		1997		63	0.61	0.24	0.11	1.00
		1998		63	0.61	0.24	0.11	1.00
		1999		63	0.61	0.24	0.11	1.00
		2000		63	0.61	0.24	0.11	1.00
		1995-00		378	0.61	0.24	0.11	1.00

Source: ECHP data set and Eurostat's Regio data set

The qualitative explanatory variables (time-invariant) organise regions into categories that are hypothesised to have some underlying similarity concerning welfare regimes, religion and family structure.

- Welfare regime: Although the level of welfare is reflected in areas such as power, industrialization and capitalist contradictions, social expenditure can be considered as a good proxy of a state's commitment to welfare (Esping-Andersen, 1990). Following the work of Esping-Andersen (1990), Ferarra (1996) and Berthoud and Iacovou (2004), we use four welfare state categories: social-democratic (Sweden, Denmark), liberal (UK, Ireland), corporatist or conservatism (Luxembourg, Belgium, France, Germany, Austria) and residual or 'Southern' (Portugal, Spain, Italy, Greece). The hypothesis here is that a country's welfare policy has an important effect on income redistribution and thus on income inequalities. The above classification assumes that a country belongs to only one welfare state regime. In reality, there is no single pure case because the Scandinavian countries, for instance, may be predominantly social democratic, but they are not free of liberal elements (Esping-Andersen, 1990, p.28).

- Religion: European regions' religious affiliation is classified into four categories[7]: mainly Protestant (Sweden, Denmark, Northern Germany, Scotland), mainly Catholic (France, Ireland, Luxembourg, Portugal, Spain, Italy, Austria, Southern Germany, Belgium), mainly Anglican (England) and mainly Orthodox (Greece). It is hypothesised that regions with the same religion have close social links so at to have similar income inequality levels within-groups of religion, but different inequality between-groups.

- Family structure: Following the work of Berthoud and Iacovou (2004), we use three groups of countries in the study of living arrangement: Nordic (Sweden, Denmark), North/Central (UK, Belgium, Luxembourg, France, Germany, Austria) and Southern/Catholic (Ireland, Portugal, Spain, Italy, Greece). The hypothesis is that a country's family structure plays a significant role in income inequality.

There is a strong overlap between the classification systems. For instance, social democratic welfare state category perfectly overlaps with Nordic family structure one. Therefore it is not possible to discern whether differences among categories are

[7] Sources: http://www.cia.gov/cia/publications/factbook;
http://commons.wikimidia.org/wiki/Image:Europe_religion_map_de.png;
http://csi-int.org/world_map_europa_religion.php

attributable to welfare state, religion or family structure (Berthoud and Iacovou, 2004, p.9).

5. Regression results

The empirical analysis exploits the panel structure of the dataset, for the 102 EU regions included in the analysis over the period 1995-2000, using pooled OLS, FEs and REs estimation of the static models and by GMM estimation of the dynamic models taking into account the unobserved regional-specific effects. We first report the static regression models and then the dynamic ones.

5.1 Estimations of the static model

Table 5.1 reports the static regression results. Three types of static econometric models are used: pooled OLS (column a), FEs (column b) and REs (column c). In all the regressions, the p-values of Breusch and Pagan's Lagrange multiplier test strongly reject the validity of the pooled OLS models. The OLS coefficient estimates are affected by heterogeneity bias. We then address the heterogeneity bias problem with FEs and REs estimates. The p-values of Hausman's test reject the GLS estimator as an appropriate alternative to the FEs estimator. The distinction between FEs and REs models is an erroneous interpretation (Greene, 2000). According to the specification tests, FEs models are the most appropriate. Finally, there is no much difference between the significance of the homoskedasticity and the heteroskedasticity consistent covariance matrix estimator. Thus the determinants of income inequality are not sensitive to the model specification about the error term.

In Regression 1 the impact of income per capita (IMN) on income inequality $(IGE1)$ is analysed. 1a, 1b and 1c equations are unconditioned by any other effects. In OLS regression (1a equation), the coefficient of IMN is negative, which suggests that an increase in 1000 Euro of income per capita are associated with, on average, about 0.0253 less income inequality measured by Theil index. In 1b equation, the relationship between income per capita and inequality is negative as well, but it is not statistically significant. The adjusted R-squared shows that income per capita does not explain any variation in income inequality in the sample. In terms of goodness-of-fit, it is likely to indicate a poor unconditioned model. In the REs unconditioned model (1c equation) income per capita is negatively correlated with income inequality and is statistically significant. Yet the negative association between income per capita and income inequality is, however, sensitive to the inclusion of additional explanatory variables. While in the pooled OLS conditional regressions the association remains negative. This behaviour corresponds to the declining segment of the Kuznets' curve. The link between income and inequality becomes negative for relatively wealthy regions, when a large percentage of workers becomes employed in high value added jobs. In the FEs and REs conditional regressions income per capita is, in contrast, positively correlated with income inequality. In all regressions, the coefficients for income per capita are very low. These findings indicate that the effect of income per capita on inequality is not robust as it is sensitive to the model specification. The relationship between both factors is offset or reinforced by the other explanatory variables. Factors that offset this positive relationship are education inequality $(EGE1)$, the average age of respondents (AGE), the unemployment level $(UNEM)$ and the inactivity level $(INACTIVE)$. In contrast, the relationship is negative, and reinforced by the labour force stock $(LFSTOCK)$, the educational attainment (EMN), the economic activity of the total population $(ECACRA)$ and that of female participation in the labour force $(ECACRF)$ and the urbanization degree $(URBANDPA)$ (Appendix A.2). Taking into account that FEs models are the most appropriate, the relationship between income inequality and income per capita is negative (Regression 3-8).

The next step of analysis is the introduction of human capital distribution measured by educational attainment and educational inequality. First, OLS regressions (2a, 3a and 4a equations) imply that the higher the educational attainment, the lower the income inequality. These regressions point in the direction that regional educational achievement has a positive influence on the resulting income distribution. A higher educational attainment increases the occupational choices and the earning opportunities of the population as a whole, making societies more egalitarian. Education seems to facilitate numerous favourable changes for individuals, because it reflects abilities, choices and preferences (Hannum and Buchman, 2005). Besides, compulsory education is publicly and freely provided in all European countries. The negative correlation between income inequality and educational attainment is also likely to reflect a ‘wage compression’ effect, whereby the supply is larger than the demand of educated labour. Adding, however, more control variables (4c, 6a, 6c, 7a, 8a, 8c, 10a and 10c equations), the impact of educational attainment on income inequality is positive. This positive correlation is likely to depict the ‘composition’ effect (Knight and Sabot, 1983). An increase in the levels of education of the population tends to increase income inequality as the imperfect competition for positions requiring advanced educational credentials increases the wages of educated people even more. In all models, the educational attainment coefficients of FEs regressions are not statistically significant. Our empirical results also show that a highly unequal distribution of education level completed is associated to higher income inequality. This relationship is robust and statistically significant. A greater share of highly educated workers within a region may signal to the employers that those with less education have lower ability, which may also lead to larger wage between high-educated and low-educated workers and thus higher income inequality. Another explanation is that the demand for unskilled labour is growing at a slower rate than the demand for skilled labour. Hence, the positive relationship seems to interpret the responsiveness of the EU labour market to differences in qualifications and skills.

The remaining regressions include the control variables described earlier. Regression 3 tests for the influence of the average age of respondents. The fact that age matters for income inequality is hardly surprising, as regions with a younger population will also tend to have a lower rate of participation in the labour force and young people in work will earn less in la labour market that rewards seniority (Higgins and Williamson, 1999).

In order to capture the economic activity characteristics of the regions, the percentage of normally working respondents (micro approach of economic activity) and the economic activity rate of total population (macro approach of economic activity) are included in Regression 4 and 5, respectively. As expected, both variables are negatively associated with income inequality and are statistically significant. The higher the level of the economic activity of a region, the lower the income inequality, reflecting that one of the main factors determining income inequality is access to work.

This point is further confirmed by the introduction of unemployment (*UNEM*) and inactivity levels (*INACTIVE*) within a region, as well as by participation in the labour market by sex (*ECACRF*) in Regressions 6 and 7 respectively. The results indicate that high unemployment and inactivity are associated with higher income inequality. Increases in unemployment and inactivity aggravate the relative position of low-income groups, because marginal workers with the relatively low skills are at the bottom of the income distribution and their jobs are at greater risk during an economic downturn (Mocan, 1995). Additionally, unemployment insurance, welfare benefits and other forms of income support are not enough to offset the loss on income due to the transitory unemployment. In other words, income received through a government transfer payments is lower than the income earned through employment. The effect of unemployment and inactivity on income inequality also reflects the inflexibility of the European labour market. European labour conditions, such as the degree of centralization in wage bargaining, the existence of a minimum wage, the differences among countries with regard to recruitment and dismissal legislation and the differences among the European countries concerning unemployment benefit, job-creation policies and vocational training programmes (Ayala *et al*., 2002), represent an important factor for the differences observed in income inequality across European regions. From a broader perspective, the high structural unemployment which characterises most European societies is likely to cause loss of current output and fiscal burden, loss of freedom and social exclusion, skill loss and long-run damage, psychological harm, ill health, motivational loss, and organisational inflexibility among others, which in turn increase income inequality (Sen, 1997). The coefficients for female economic activity rate in all regressions are negative and significant. The impact of the increase in female economic activity rate (Table 4.1) has been to lessen the trend toward greater income inequality caused by aspects of social change during the period of analysis (Ryscavage *et al.*, 1992).

In Regression 8, we include urbanisation. The correlation between urbanisation and inequality is negative. These results underline that European societies are located in the the declining segment of the Kuznets curve. This rejects Estudillo's hypothesis (1997) that the heterogeneity of urban areas enhances, rather than lowers, inequality. Highly urbanised regions seem not only to be more economically prosperous – the correlation between *IMN* and *URBANDPA* is positive (0.46) – but also to have less inequality, as a consequence of the negative relationship between income per capita and inequality.

We finally estimate the impact of the qualitative explanatory variables on income inequality[8]. FEs estimator is not provided because there is no any within-group variation in the dummy variables. In Regression 9, the omitted category is social-democratic welfare states. The regression results show that all welfare regimes are important determinants of income inequality. Social-democratic welfare states, which in theory promote a higher standard of equality, have indeed lower income inequality than conservative welfare states in which private insurance and occupational benefits play a truly marginal role and corporatism displaces the market as a provider of welfare (Esping-Andersen, 1990). Social-democratic welfare states are more egalitarian than corporatist ones because, in the former, the welfare state minimises dependence on the family and allows women greater freedom to choose work rather than to stay at home, while, in the latter, state intervention is more modest and kicks off mainly when the family's capacity to service its members becomes exhausted (Esping-Andersen, 1990). Corporatist welfare states have lower income inequality than liberal welfare states in which '*means-tested assistance, modest universal transfers, or modest social insurance plans predominate*' (Esping-Andersen, 1990, p.26). The latter also are more egalitarian than 'Southern' (or residual) welfare states.

Regression 10 introduces religion as an explanatory variable. We use mainly Protestant regions as our base category. All categories seem to be important determinants of income inequality, with mainly Protestant regions having a higher income inequality than Catholic ones which, in turn, are more egalitarian than Anglican ones (10c equation). Orthodox regions have the most inegalitarian societies. Finally, it is interesting to note that all family structure and living arrangements categories affect income inequality significantly (Regression 11). Nordic family structure regions are the most egalitarian societies and Southern/Catholic have the highest inequality.

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[8] See Appendix A.3 dummy variables definition.

Considering the standardised coefficients of the above regressions (Appendix A.4)[9], female economic activity rate explains the largest variation in income inequality and is also robust to specification model. The impact of both micro and macro approaches of economic activity on income inequality is high as well. In contrast, the average age of respondents, the level of urbanisation, the liberal welfare state, Anglicanism, and Nordic family explain only a relative small part of the total variation in income inequality.

---------- Insert Table 5.1: Static regression model ----------

5.2 Estimations of the dynamic model

Table 5.2 presents results for the dynamic income inequality equations (Arellano-Bond estimator). The first column of each model specification assumes that the explanatory variables are strictly exogenous. The last two columns show the GMM results for the same model specification regarding that the explanatory variables are predetermined (column b) or endogenous (column c). All the parameters are short-run, while the long-run ones are reported at the bottom of each regression at the table. Therefore, by employing a dynamic panel data approach, we can distinguish between the short-run and the long-run evolution of the income inequality determinants in the EU.

First of all, if the explanatory variables, on the one hand, are strictly exogenous, the specification tests are satisfactory. More specifically, the tests regarding serial correlation reject the absence of first order, but not second order serial correlation in both the homoskedastic and robust case. The Sargan test statistics of overidentifying restrictions do not indicate correlation between the instruments and the error term. If the explanatory variables, on the other, are predetermined (except for the average age of respondents), the specification tests are not satisfactory enough. There is significant negative serial correlation in the first differenced residuals of first order in both the homoskedastic and robust case but not of the second order, except for Regression 6b where the second order serial correlation is rejected in the homoskedastic case. Additionally, the Sargan tests indicate correlation between the instruments and the error term of the first-differenced

[9] The standardized coefficient is the standard deviation change in the dependent variable caused by one standard deviation change in each explanatory variable.

equation. Finally, if the explanatory variables are assumed to be endogenous (except for the average age of respondents), our estimates perform well based on the specification tests. The tests regarding serial correlation, once again, reject the absence of first order serial correlation in both homoskedastic and robust estimator of the variance-covariance matrix of the parameter estimates, but not the second order serial correlation except for Regression 6c in the homoskedastic case. Although the size of the instrument matrix increases quickly when the explanatory variables are endogenous, the Sargan tests do not indicate correlation between the instruments and the error term of the first-differenced equation. Taking into account the specification tests applied to the estimated dynamic models, 6c equation (homoskedastic case) where the explanatory variables are endogenous is the most appropriate. In this equation, there is significant negative serial correlation in the first-differenced residuals of both first order and second order.

Generally speaking, the exogenous, predetermined and endogenous parameters are similar to each other, denoting the robustness of the dynamic results. First, all equations reject the lagged income inequality coefficient is zero. The coefficient of lagged dependent variable is higher when the explanatory variables are assumed to be exogenous except for Regression 1. Additionally, the coefficients of the lagged dependent variable are statistically significant at the 1% level in both homoskedastic and robust case. It was expected to find that income inequality in the current period depends on income inequality of the previous period. The rationale for this result is simple, because income inequality does not change very quickly over one year and job mobility which is the main source of their personal income is rather low, for psychological, technological and institutional reasons.

Regression 1 depicts that income inequality increases in the short-run as the current income per capita increases thus leading to a positive correlation between the two variables, while the correlation between the lagged income per capita and income inequality is negative and statistically significant only when income per capita is assumed to be a strictly exogenous variable. Besides, the long-run coefficients are positive and statistically significant in most equations. For instance, if the strictly exogenous income is increased by 1%, income inequality will rise by 0.0139 in the short-run and 0.0331 in the long-run. This rejects the declining segment of the Kuznets curve, but is likely to accept Lydall's (1977) hypothesis that only a limited number of people can be transferred to higher levels of skills, while the remainder have to wait their turn.

The results also indicate that income inequality declines over time for a region as the current human capital variables (educational attainment and human capital inequality) decline and as the lagged ones increase. Both the current and the lagged human capital variables are statistically significant in most equations. According to the estimated value and assuming, for example, that human capital variables are endogenous, a 1% increase in coefficient of educational attainment would lead in the short-run to a 0.2503% increase and in the long-run to a 0.3018% increase in the level of income inequality (Regression 2). Additionally, due to the negative relationship between the lagged educational achievement and income inequality, the latter reacts to the European labour market with a lag of one year. The European labour market decisions and the effectiveness of the European social system take time to implement, since the educated labour supply is relatively more expanded to lagged demand. The effects of educational attainment and educational inequality obtained after full adjustment of income inequality (the long-run effects) are positive and statistically significant only when education is endogenous (2c, 3c and 4c equation). The negative long-run relationship between income and educational inequality highlights the responsiveness of EU labour market to differences in qualifications and skills.

The short-run coefficient of the current average age of respondents within a region is positively correlated with income inequality and with very low statistical significance (Regression 3). However, the current effect of AGE is slight. Alternatively, the lagged average age is negatively correlated with income inequality but not statistically significant. The long-run effect of average age on inequality is positive which could reflect that with greater longevity, there will be a growing number of elderly people and since their income is lower than the young, an increasing number of elderly people should lead to a rise in the number of households with low income (Estudillo, 1997, p. 68), but this variable is not statistically significant.

Regression 4 (4a and 4b equation) shows that the labour force stock has a positive effect on income inequality, but is not statistically significant. Nevertheless, the impact of economic activity has the expected sign (negative) and is statistically significant at the 1% level in the long-run (Regression 5). High unemployment is associated with higher inequality in the long-run (6c equation). This outcome is consistent with the outcome of the static regression models denoting the robustness of the relationship between unemployment and inequality. The dynamic models are likely to allow testing whether changes in the short-term (cyclical) and long-term (structural) unemployment influence changes in income inequality. The short-run and long-run impact of unemployment on inequality has the right sign with respect to the literature and the static regression models. Finally, the impact of the female economic activity rate on income inequality is negative and statistically significant no matter what this explanatory variable is assumed to be.

To sum up, 6c equation performs well based on the specification tests. In this equation, the unemployment and the female participation in the labour force are the most significant factors determining income inequality within European regions. More specifically, the higher the unemployment level, the higher the income inequality; and the higher the female participation, the lower the income inequality.

---------- Insert Table 5.2: Dynamic regression model ----------

6. Concluding remarks and further research

Different static and dynamic panel data analyses have been conducted in order to examine how microeconomic changes in human capital distribution in terms of both educational attainment and educational inequality affect the short-term evolution of income inequality across regions of the EU over the period 1995-2000. Our methodology incorporates variability both across regions and over time. The advantage of dynamic over static models is that persistence over time is not only due to the unobserved regional-specific effects, but also due to the presence of a lagged income inequality among the regressors. Autoregressive models highlight the persistence in income inequality, because income distribution does not change quickly over time. Since the estimated coefficient of the lagged dependent variable is high and significant in all dynamic specifications, the estimated long-run coefficients of the explanatory variables are less efficient and biased.

Taking into account the specification tests applied to the estimated models, the relationship between income per capita and income inequality seems to be positive. If so, income per capita does not alleviate the inequality increase, rejecting the declining segment of the Kuznets curve. Considering the FEs models which are the most appropriate in static analysis, our results show that, while the impact of educational attainment on income inequality is not clear, educational inequality is associated with higher income inequality. The dynamic models show that, in the long-run, both educational attainment and educational inequality are positively associated with inequality, but this relationship is statistically significant only when the explanatory variables are endogenous. The impact of the average age of respondents and inactivity within a region on income inequality is sensitive to the specification model. Unemployment is positively associated to income inequality. Taking into account the urbanisation level, an increasing weight of the urban relative to the rural population means a decreasing income inequality. The economic activity rate is negatively associated with the observed income inequality. Finally, our results show that the social democratic welfare states, the mainly Protestant regions and those with Nordic family structures are among the most egalitarian.

Our results have important policy implications as they shed light on the ambiguous impact of income per capita on income inequality. They show that improving access to education, providing higher quality of education, and generally, increasing educational attainment may have not any effect on income inequality. They also indicate that income and human capital inequality are synonymous, highlighting the responsiveness of the EU labour market to differences in qualifications and skills.

Although our methodology seems to address the question of how changes in income per capita, educational attainment and education inequality affect the observed income inequality, further research is needed. The fact that only a limited time period is available advises caution when interpreting the results. Longer time series will reinforce the analysis, as would the use of other inequality indices, such as the Gini coefficient, the relative mean deviation index, or the squared coefficient of variation, in order to check the sensitivity of inequality indexes. Another suggestion for further research is that dynamic models can also be estimated by Arellano-Bover and Blundell-Bond estimator (Arellano and Bover, 1995; Blundell and Bond, 1998).

A potential limitation of our analysis – which is also a limitation in most cross-sectional studies – is the fact that regions are more homogeneous than countries, because the regions are subunits of a single national entity (Nielson and Alderson, 1997). Regions cannot cover as wide a range of variation in income and human capital distribution, in levels of economic development and in some unobserved characteristics such as institutions and socio-cultural conditions as a cross-national sample. Regional boundaries may not define autonomous and internally integrated socioeconomic systems with respect to distributional process (Nielson and Alderson, 1997). Thus the administrative boundaries used to organise the data series do not coincide perfectly with the actual boundaries, arising spatial autocorrelation into data (Anselin and Rey, 1991). A spatial autocorrelation analysis may indicate whether income inequality and its determinants are randomly distributed over space or there are similarities among regions.

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Appendix A.1: Descriptive statistics of ECHP data set

Year	Statistic	Quantitative variables			Qualitative variables			
					Main activity status			
		Income	Educational attainment	Age	Unemployed	Inactive	Normally working	Urbanisation
1995	Obs	120413	119463	125395	7915	55169	61406	26863
	Mean	9744.58	0.60	44.96				
	Percentage				6.36	44.32	49.33	46.68
	Std. Dev.	11782.83	0.73	18.23				
	Variance	1.39E+08	0.53	332.35				
	Skewness	8.39	0.78	0.34				
	Kurtosis	311.52	2.27	2.12				
1996	Obs	124663	114529	120413	7685	58933	53214	26863
	Mean	10163.60	0.60	45.05				
	Percentage				6.41	44.41	49.18	46.68
	Std. Dev.	11234.33	0.73	18.28				
	Variance	1.26E+08	0.53	334.28				
	Skewness	6.45	0.79	0.35				
	Kurtosis	205.83	2.27	2.12				
1997	Obs	117886	118402	124756	7760	54183	62221	26863
	Mean	10472.71	0.62	45.22				
	Percentage				6.25	43.64	50.11	46.68
	Std. Dev.	11529.87	0.74	18.32				
	Variance	1.33E+08	0.55	335.47				
	Skewness	6.87	0.73	0.34				
	Kurtosis	213.47	2.17	2.13				
1998	Obs	113455	115953	117980	6775	50646	59978	26863
	Mean	10617.48	0.68	45.54				
	Percentage				5.77	43.14	51.09	46.68
	Std. Dev.	12648.77	0.76	18.32				
	Variance	1.60E+08	0.57	335.66				
	Skewness	16.09	0.60	0.34				
	Kurtosis	1049.18	1.97	2.13				
1999	Obs	108731	112406	113536	5908	48802	58342	26863
	Mean	11037.64	0.68	45.78				
	Percentage				5.23	43.17	51.61	46.68
	Std. Dev.	13552.43	0.77	18.33				
	Variance	1.84E+08	0.59	336.04				
	Skewness	30.58	0.63	0.33				
	Kurtosis	3616.64	1.96	2.13				
2000	Obs	104953	107751	108848	5165	46890	56384	26863
	Mean	11368.55	0.69	46.07				
	Percentage				4.76	43.24	52	46.68
	Std. Dev.	12884.93	0.77	18.45				
	Variance	1.66E+08	0.59	340.32				
	Skewness	10.55	0.59	0.32				
	Kurtosis	442.83	1.92	2.12				

Appendix A.2: Correlation matrices

Correlations: Regression 2

	imn	emn	ege1
imn	1.0000		
emn	0.7797	1.0000	
ege1	-0.7368	-0.8691	1.0000

Correlations: Regression 3

	imn	emn	ege1	age
imn	1.0000			
emn	0.7797	1.0000		
ege1	-0.7368	-0.8691	1.0000	
age	-0.0802	-0.1744	0.2018	1.0000

Correlations: Regression 4

	imn	emn	ege1	age	lfstock
imn	1.0000				
emn	0.7797	1.0000			
ege1	-0.7368	-0.8691	1.0000		
age	-0.0802	-0.1744	0.2018	1.0000	
lfstock	0.6323	0.6020	-0.4173	-0.1360	1.0000

Correlations: Regression 5

	imn	emn	ege1	age	ecacra
imn	1.0000				
emn	0.7648	1.0000			
ege1	-0.7114	-0.8595	1.0000		
age	-0.0203	-0.1005	0.1137	1.0000	
ecacra	0.6149	0.6409	-0.4326	-0.0112	1.0000

Correlations: Regression 6

	imn	emn	ege1	age	unem	ecacrf
imn	1.0000					
emn	0.7648	1.0000				
ege1	-0.7114	-0.8595	1.0000			
age	-0.0203	-0.1005	0.1137	1.0000		
unem	-0.4289	-0.2012	0.0517	-0.2562	1.0000	
ecacrf	0.6533	0.6734	-0.4806	0.0731	-0.4395	1.0000

Correlations: Regression 7

	imn	emn	ege1	age	inactive	ecacrf
imn	1.0000					
emn	0.7648	1.0000				
ege1	-0.7114	-0.8595	1.0000			
age	-0.0203	-0.1005	0.1137	1.0000		

inactive	-0.6222	-0.6940	0.5607	0.2748	1.0000	
ecacrf	0.6533	0.6734	-0.4806	0.0731	-0.7831	1.0000

Correlations: Regression 8

	imn	emn	ege1	age	unem	ecacrf	urbandpav
imn	1.0000						
emn	0.8672	1.0000					
ege1	-0.7493	-0.8337	1.0000				
age	-0.0349	-0.0791	0.1096	1.0000			
unem	-0.4876	-0.3679	0.1555	-0.2999	1.0000		
ecacrf	0.7146	0.6233	-0.3360	0.0642	-0.7437	1.0000	
urbandpav	0.4553	0.4530	-0.2332	-0.0281	-0.3525	0.4603	1.0000

Appendix A.3: Dummy variables definition

Variable	Definition
Welfare state	
DWSSOC	Socialism (social democratic)
DWSLIB	Liberal
DWSCORP	Corporatist (conservatism)
DWSRES	Residual ('Southern')
Religion	
DRLPROT	Mainly Protestant
DRLCATH	Mainly Catholic
DRLORTH	Mainly Orthodox
DRLANGL	Mainly Anglicans
Family structure	
DFNORD	Nordic (Scandinavian)
DFNC	North/Central
DFSC	Southern/Catholic

Appendix A.4: Standardised coefficients

DEPENDENT VARIABLE: IGE1 (1995-2000) beta coefficient (OLS)											
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9	REGR. 10	REGR. 11
IMN	-0.6514	-0.3659	-0.3360	-0.0449	-0.1675	-0.0845	-0.1105	-0.2136	0.1853	0.0119	0.2155
EMN		-0.5168	-0.5331	-0.1467	0.0171	0.0877	0.1149	0.1418	0.0544	0.1875	0.0672
EGE1		-0.1598	-0.1185	0.2067	0.2553	0.2854	0.2460	0.1985	0.2357	0.3940	0.2484
AGE			-0.1662	-0.2178	-0.1712	-0.0964	-0.1661	-0.0537	-0.1017	-0.1401	-0.0959
LFSTOCK				-0.5644							
ECACRA					-0.5712						
UNEM						0.0531		0.1887	0.0971	0.0656	0.1132
INACTIVE							0.1974				
ECACRF						-0.6773	-0.5612	-0.5035	-0.4992	-0.6110	-0.4832
URBANDPAV (fixed)								-0.1148			
DWSLIB									0.1024		
DWSCORP									0.1144		
DWSRES									0.5353		
DRLCATH										0.1310	
DRLORTH										0.2146	
DRLANGL										-0.0295	
DFNORD											-0.0641
DFSC											0.4668

DEPENDENT VARIABLE: IGE1
(1995-2000)

	REGRESSION 1			REGRESSION 2			REGRESSION 3			REGRESSION 4		
	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs
IMN	-0.0253 (0.0012)*** (0.0014)***	-0.0001 (0.0011) (0.0013)	-0.0036 (0.0011)*** (0.0013)***	-0.0140 (0.0018)*** (0.0021)***	0.0016 (0.0014) (0.0016)	-0.0012 (0.0014) (0.0015)	-0.0129 (0.0018)*** (0.0020)***	0.0026 (0.0014)* (0.0017)	-0.0009 (0.0015) (0.0016)	-0.0017 (0.0016) (0.0018)	0.0033 (0.0014)** (0.0017)*	0.0008 (0.0015) (0.0015)
EMN				-0.2817 (0.0355)*** (0.0304)***	0.0396 (0.0305) (0.0316)	0.0371 (0.0304) (0.0339)	-0.2906 (0.0347)*** (0.0285)***	0.0394 (0.0303) (0.0318)	0.0370 (0.0305) (0.0340)	-0.0800 (0.0312)** (0.0263)***	0.0466 (0.0301) (0.0309)	0.0658 (0.0298)*** (0.0310)***
EGE1				-0.0556 (0.0210)*** (0.0199)***	0.0723 (0.0230)*** (0.0231)***	0.0847 (0.0222)*** (0.0267)***	-0.0412 (0.0206)*** (0.0179)***	0.0732 (0.0229)*** (0.0232)***	0.0879 (0.0223)*** (0.0268)***	0.0719 (0.0183)*** (0.0167)***	0.0685 (0.0227)*** (0.0223)***	0.0901 (0.0213)*** (0.0244)***
AGE							-0.0130 (0.0023)*** (0.0024)***	-0.0057 (0.0022)** (0.0024)**	-0.0042 (0.0022)* (0.0025)*	-0.0170 (0.0019)*** (0.0019)***	-0.0059 (0.0022)*** (0.0026)**	-0.0056 (0.0021)*** (0.0027)***
LFSTOCK										-1.1632 (0.0693)*** (0.0676)***	-0.2765 (0.0837)*** (0.0981)***	-0.6963 (0.0788)*** (0.0895)***
ECACRA												
UNEM												
INACTIVE												
ECACRF												
URBANDPAV (fixed)												
YR96*URBAND PAV												
YR97*URBAND PAV												
YR98*URBAND PAV												
YR99*URBAND PAV												
YR00*URBAND PAV												
CONSTANT	0.6660 (0.0144)*** (0.0165)***	0.3821 (0.0121)*** (0.0151)***	0.4183 (0.0166)*** (0.0189)***	0.7956 (0.0414)*** (0.0443)***	0.2787 (0.0382)*** (0.0396)***	0.2974 (0.0393)*** (0.0473)***	1.3667 (0.1087)*** (0.1136)***	0.5255 (0.1022)*** (0.1072)***	0.4826 (0.1027)*** (0.1212)***	1.7911 (0.0930)*** (0.0879)***	0.6732 (0.1106)*** (0.1220)***	0.8712 (0.1078)*** (0.1379)***
ADJ R-SQ	0.4233	0.0000		0.4890	0.0313		0.5144	0.0445		0.6709	0.0654	
OBS.	604			596			596			596		
LM TEST (p-value)	916.46 (0.0000)			715.20 (0.0000)			645.03 (0.0000)			634.09 (0.0000)		
HAUSMAN TEST (p-value)	■ 71.46 (0.0000)			■ 289.07 (0.0000)			■ 35.86 (0.0000)			■ 87.27 (0.0000)		

NOTES: OLS indicates ordinary least squares estimation without group dummy variables (OLS estimation of pooled data). FEs indicates fixed effects model based on mean centered data. REs indicates random effects model (GLS coefficients). (*), (**), and (***) indicates significance at the 10%, 5% and 1% level, respectively. *(*)*, *(**)*, and *(***)* denotes the significance of the White (1980) estimator (robust standard errors). LM TEST is the Lagrange multiplier test for the random effects model based on the OLS residuals (Breusch and Pagan, 1980). HAUSMAN TEST is the Hausman test for fixed or random effects (Hausman, 1978). ■ denotes model fitted on non-robust (or robust) estimator fails to meet the asymptotic assumptions of the Hausman test; so we choose the robust (or non-robust) estimator.

	REGRESSION 5			REGRESSION 6			REGRESSION 7			REGRESSION 8		
	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs
IMN	-0.0065 (0.0015)*** (0.0016)***	0.0029 (0.0016)* (0.0017)*	-0.0001 (0.0015) (0.0015)	-0.0033 (0.0015)** (0.0017)*	0.0046 (0.0016)*** (0.0017)***	0.0020 (0.0015) (0.0015)***	-0.0043 (0.0014)*** (0.0014)***	0.0039 (0.0016)** (0.0018)**	0.0014 (0.0015) (0.0015)	-0.0076 (0.0024)*** (0.0028)***	0.0110 (0.0025)*** (0.0027)***	0.0020 (0.0017) (0.0017)
EMN	0.0097 (0.0331) (0.0315)	0.0018 (0.0306) (0.0293)	0.0175 (0.0286) (0.0293)	0.0498 (0.0298)* (0.0288)*	0.0136 (0.0298) (0.0276)	0.0359 (0.0275) (0.0270)***	0.0652 (0.0295)** (0.0286)**	0.0101 (0.0305) (0.0285)	0.0386 (0.0278) (0.0278)	0.0710 (0.0375)* (0.0381)*	0.0222 (0.0396) (0.0415)	0.0697 (0.0318)** (0.0342)**
EGE1	0.0961 (0.0189)*** (0.0181)***	0.0313 (0.0224) (0.0197)	0.0519 (0.0202)** (0.0205)**	0.1074 (0.0175)*** (0.0166)***	0.0330 (0.0218) (0.0184)*	0.0600 (0.0193)*** (0.0182)***	0.0926 (0.0166)*** (0.0152)***	0.0361 (0.0222) (0.0188)*	0.0591 (0.0194)*** (0.0181)***	0.0700 (0.0217)*** (0.0185)***	0.0831 (0.0302)*** (0.0374)**	0.0802 (0.0255)*** (0.0282)***
AGE	-0.0138 (0.0019)*** (0.0018)***	-0.0082 (0.0022)*** (0.0025)***	-0.0078 (0.0020)*** (0.0021)***	-0.0078 (0.0018)*** (0.0018)***	-0.0053 (0.0022)** (0.0025)**	-0.0044 (0.0020)** (0.0020)***	-0.0134 (0.0020)*** (0.0022)***	-0.0073 (0.0022)*** (0.0024)***	-0.0069 (0.0020)*** (0.0022)***	-0.0041 (0.0023)* (0.0022)*	-0.0073 (0.0027)*** (0.0026)***	-0.0061 (0.0026)** (0.0025)**
LFSTOCK												
ECACRA	-0.0134 (0.0008)*** (0.0007)***	-0.0089 (0.0014)*** (0.0016)***	-0.0131 (0.0010)*** (0.0011)***									
UNEM				0.2519 (0.1304)* (0.1352)*	0.5541 (0.1404)*** (0.1515)***	0.3933 (0.1301)*** (0.1402)***				0.8557 (0.2080)*** (0.1794)***	0.4594 (0.2069)** (0.2305)**	0.5955 (0.2030)*** (0.2215)***
INACTIVE							0.4937 (0.1052)*** (0.1141)***	0.0084 (0.0933) (0.1080)	0.1725 (0.0882)* (0.0894)*			
ECACRF				-0.0116 (0.0006)*** (0.0005)***	-0.0068 (0.0012)*** (0.0013)***	-0.0111 (0.0008)*** (0.0008)***	-0.0096 (0.0007)*** (0.0008)***	-0.0079 (0.0012)*** (0.0013)***	-0.0110 (0.0008)*** (0.0009)***	-0.0083 (0.0010)*** (0.0009)***	-0.0020 (0.0017) (0.0017)	-0.0083 (0.0011)*** (0.0012)***
URBANDPAV (fixed)										-0.0736 (0.0215)*** (0.0211)***		-0.1538 (0.0467)*** (0.0446)***
YR96*URBAND PAV											-0.0290 (0.0148)* (0.0151)*	
YR97*URBAND PAV											-0.0453 (0.0150)*** (0.0136)***	
YR98*URBAND PAV											-0.0136 (0.0163) (0.0147)	
YR99*URBAND PAV											-0.0374 (0.0174)** (0.0170)**	
YR00*URBAND PAV											-0.0743 (0.0184)*** (0.0171)***	
CONSTANT	1.7736 (0.0943)*** (0.0815)***	1.2128 (0.1333)*** (0.1438)***	1.4366 (0.1123)*** (0.1239)***	1.1955 (0.0939)*** (0.0864)***	0.8348 (0.1195)*** (0.1213)***	0.9957 (0.1029)*** (0.1038)***	1.1734 (0.0849)*** (0.0734)***	1.0108 (0.1153)*** (0.1182)***	1.0633 (0.0991)*** (0.1038)***	0.9526 (0.1245)*** (0.1081)***	0.6300 (0.1611)*** (0.1640)***	0.9907 (0.1375)*** (0.1448)***
ADJ R-SQ	0.7139	0.1343		0.7674	0.1743		0.7755	0.1432		0.7672	0.2704	
OBS.	513			513			513			299		
LM TEST (p-value)	715.68 (0.0000)			676.43 (0.0000)			630.60 (0.0000)			322.72 (0.0000)		
HAUSMAN TEST (p-value)	46.71 (0.0000) 46.86 (0.0000)			54.24 (0.0000) 61.67 (0.0000)			73.32 (0.0000) 37.77 (0.0000)					

	REGRESSION 9			REGRESSION 10			REGRESSION 11					
	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs			
IMN	0.0072 (0.0018)*** *(0.0021)****		0.0053 (0.0015)*** *(0.0015)****	0.0005 (0.0015) *(0.0017)*		0.0030 (0.0015)** *(0.0014)***	0.0084 (0.0018)*** *(0.0020)****		0.0054 (0.0015)*** *(0.0015)****			
EMN	0.0309 (0.0338) *(0.0358)*		0.0189 (0.0272) *(0.0266)*	0.1064 (0.0340)*** *(0.0372)****		0.0496 (0.0276)* *(0.0290)**	0.0381 (0.0283) *(0.0296)*		0.0230 (0.0260) *(0.0259)*			
EGE1	0.0887 (0.0187)*** *(0.0192)****		0.0446 (0.0192)** *(0.0173)***	0.1483 (0.0188)*** *(0.0198)****		0.0684 (0.0194)*** *(0.0208)****	0.0935 (0.0164)*** *(0.0173)****		0.0477 (0.0182)*** *(0.0170)****			
AGE	-0.0082 (0.0017)*** *(0.0017)****		-0.0061 (0.0019)*** *(0.0020)****	-0.0113 (0.0018)*** *(0.0017)****		-0.0058 (0.0020)*** *(0.0020)****	-0.0077 (0.0017)*** *(0.0016)****		-0.0061 (0.0019)*** *(0.0020)****			
LFSTOCK												
ECACRA												
UNEM	0.4602 (0.1410)*** *(0.1380)****		0.5059 (0.1272)*** *(0.1374)****	0.3112 (0.1384)** *(0.1431)***		0.4550 (0.1300)*** *(0.1436)****	0.5367 (0.1264)*** *(0.1362)****		0.5122 (0.1248)*** *(0.1374)****			
INACTIVE												
ECACRF	-0.0085 (0.0007)*** *(0.0007)****		-0.0073 (0.0009)*** *(0.0009)****	-0.0104 (0.0006)*** *(0.0006)****		-0.0089 (0.0008)*** *(0.0010)****	-0.0082 (0.0007)*** *(0.0007)****		-0.0072 (0.0009)*** *(0.0009)****			
URBANDPAV (fixed)												
DWSLIB	0.0356 (0.0185)* *(0.0166)***		0.0621 (0.0284)** *(0.0241)***									
DWSCORP	0.0374 (0.0169)** *(0.0154)***		0.0594 (0.0291)** *(0.0249)***									
DWSRES	0.1814 (0.0261)*** *(0.0291)****		0.2259 (0.0357)*** *(0.0301)****									
DRLCATH				0.0408 (0.0109)*** *(0.0112)****		0.0955 (0.0221)*** *(0.0248)****						
DRLORTH				0.1584 (0.0196)*** *(0.0179)****		0.2243 (0.0411)*** *(0.0373)****						
DRLANGL				-0.0104 (0.0122) *(0.0127)*		0.0262 (0.0219) *(0.0248)*						
DFNC							-0.0402 (0.0163)** *(0.0145)****		-0.0599 (0.0265)** *(0.0222)****			
DFSC							0.1566 (0.0147)*** *(0.0179)****		0.1680 (0.0200)*** *(0.0193)****			
CONSTANT	0.8896 (0.1020)*** *(0.0997)****		0.7697 (0.1117)*** *(0.1096)****	1.1565 (0.0927)*** *(0.0873)****		0.8613 (0.1060)*** *(0.1160)****	0.8602 (0.0942)*** *(0.0922)****		0.8163 (0.1005)*** *(0.0989)****			
ADJ R-SQ	0.8022			0.7978			0.8097					
OBS.	*513*			*513*			*513*					
LM TEST (p-value)	752.96 (0.0000)			655.71 (0.0000)			740.08 (0.0000)					
HAUSMAN												

TEST (p-value)												

DEPENDENT VARIABLE: IGE1
Arellano-Bond estimator
(1995-2000)

	REGRESSION 1			REGRESSION 2			REGRESSION 3			REGRESSION 4		
	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous
$IGE1_{i,t-1}$	0.7531 (0.1234)*** (0.1199)***	0.8135 (0.1230)*** (0.1445)***	0.6965 (0.1451)*** (0.1525)***	0.8993 (0.1441)*** (0.1563)***	0.6388 (0.1232)*** (0.1743)***	0.4526 (0.1574)*** (0.2283)**	0.9188 (0.1469)*** (0.1662)***	0.6125 (0.1212)*** (0.1717)***	0.4405 (0.1543)*** (0.2289)*	0.9913 (0.1688)*** (0.1864)***	0.5709 (0.1219)*** (0.1857)***	0.4193 (0.1539)*** (0.2203)*
IMN_{it} $IMN_{i,t-1}$	0.0139 (0.0026)*** (0.0027)*** -0.0057 (0.0031)* (0.0032)*	0.0063 (0.0038)* (0.0044) -0.0014 (0.0050) (0.0042)	0.0132 (0.0042)*** (0.0050)*** -0.0017 (0.0065) (0.0045)	0.0175 (0.0032)*** (0.0033)*** -0.0109 (0.0045)** (0.0048)**	0.0202 (0.0055)*** (0.0061)*** -0.0089 (0.0068) (0.0081)	0.0239 (0.0058)*** (0.0064)*** -0.0108 (0.0075) (0.0085)	0.0184 (0.0033)*** (0.0035)*** -0.0124 (0.0047)*** (0.0054)**	0.0204 (0.0055)*** (0.0056)*** -0.0071 (0.0068) (0.0074)	0.0241 (0.0058)*** (0.0061)*** -0.0103 (0.0073) (0.0081)	0.0181 (0.0034)*** (0.0036)*** -0.0137 (0.0050)*** (0.0061)**	0.0195 (0.0051)*** (0.0052)*** -0.0035 (0.0066) (0.0069)	0.0231 (0.0055)*** (0.0053)*** -0.0108 (0.0076) (0.0067)
EMN_{it} $EMN_{i,t-1}$				0.0901 (0.0518)* (0.0493)* -0.1282 (0.0504)** (0.0494)***	0.1584 (0.0775)** (0.0913)* -0.1375 (0.0503)*** (0.0448)***	0.2503 (0.0846)*** (0.1029)** -0.0850 (0.0701) (0.0687)	0.1004 (0.0521)* (0.0517)* -0.1412 (0.0513)*** (0.0520)***	0.1577 (0.0763)** (0.0873)* -0.1423 (0.0498)*** (0.0439)***	0.2517 (0.0842)*** (0.0995)** -0.0895 (0.0694) (0.0694)	0.0950 (0.0540)* (0.0530)* -0.1465 (0.0531)*** (0.0543)***	0.1478 (0.0703)** (0.0755)* -0.1316 (0.0492)*** (0.0416)***	0.2666 (0.0829)*** (0.0843)*** -0.0900 (0.0688) (0.0711)
$EGE1_{it}$ $EGE1_{i,t-1}$				0.0587 (0.0346)* (0.0256)** -0.0720 (0.0357)** (0.0249)***	0.1006 (0.0479)** (0.0419)** -0.0677 (0.0370)* (0.0264)**	0.1275 (0.0572)** (0.0551)** -0.0342 (0.0506) (0.0465)	0.0560 (0.0352) (0.0258)** -0.0735 (0.0361)** (0.0265)***	0.1029 (0.0478)** (0.0433)** -0.0658 (0.0366)* (0.0259)**	0.1293 (0.0567)** (0.0559)** -0.0364 (0.0502) (0.0468)	0.0560 (0.0363) (0.0266)** -0.0772 (0.0374)** (0.0280)***	0.1124 (0.0437)** (0.0398)*** -0.0601 (0.0350)* (0.0240)**	0.1524 (0.0550)*** (0.0522)*** -0.0384 (0.0483) (0.0472)
AGE_{it} $AGE_{i,t-1}$							0.0092 (0.0049)* (0.0054)* -0.0011 (0.0033) (0.0036)	0.0082 (0.0045)* (0.0050)* -0.0035 (0.0027) (0.0030)	0.0081 (0.0044)* (0.0051) -0.0010 (0.0028) (0.0030)	0.0100 (0.0051)* (0.0057)* -0.0018 (0.0034) (0.0038)	0.0077 (0.0044)* (0.0052) -0.0041 (0.0028) (0.0030)	0.0073 (0.0045) (0.0051) -0.0004 (0.0030) (0.0030)
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										0.2505 (0.1565) (0.1739) 0.0726 (0.1291) (0.1161)	0.1588 (0.2936) (0.3475) -0.1505 (0.1747) (0.1589)	-0.2972 (0.3870) (0.4391) 0.2316 (0.3129) (0.3589)
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$												

$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	400			392			392			392		
SARGAN TEST (p-value)	12.26 (0.1989)	26.20 (0.0709)	18.09 (0.1541)	10.67 (0.2988)	49.79 (0.0306)	32.29 (0.0547)	9.54 (0.3888)	48.36 (0.0412)	31.29 (0.0690)	9.29 (0.4107)	59.13 (0.0331)	35.24 (0.0840)
AR(1) TEST (p-value)	-5.85 (0.0000) *-4.42* *(0.0000)*	-6.11 (0.0000) *-4.29* *(0.0000)*	-4.82 (0.0000) *-4.09* *(0.0000)*	-5.64 (0.0000) *-3.82* *(0.0001)*	-5.39 (0.0000) *-3.58* *(0.0003)*	-3.44 (0.0006) *-2.32* *(0.0202)*	-5.72 (0.0000) *-3.77* *(0.0002)*	-5.35 (0.0000) *-3.47* *(0.0005)*	-3.40 (0.0007) *-2.24* *(0.0254)*	-5.57 (0.0000) *-3.72* *(0.0002)*	-5.33 (0.0000) *-3.37* *(0.0008)*	-3.61 (0.0003) *-2.51* *(0.0120)*
AR(2) TEST (p-value)	-1.19 (0.2339) *-0.68* *(0.4977)*	-1.38 (0.1671) *-0.79* *(0.4289)*	-1.14 (0.2562) *-0.65* *(0.5188)*	-1.45 (0.1480) *-0.85* *(0.3941)*	-1.35 (0.1783) *-0.83* *(0.4078)*	-0.89 (0.3725) *-0.60* *(0.5470)*	-1.28 (0.2018) *-0.74* *(0.4573)*	-1.23 (0.2193) *-0.73* *(0.4679)*	-0.78 (0.4356) *-0.51* *(0.6100)*	-1.17 (0.2428) *-0.68* *(0.4996)*	-1.11 (0.2680) *-0.63* *(0.5274)*	-0.96 (0.3361) *-0.69* *(0.4912)*
Long-run parameters												
IMN	0.0331 (0.0137)** *(0.0143)***	0.0266 (0.0200) *(0.0189)*	0.0377 (0.0136)*** *(0.0151)***	0.0654 (0.0890) *(0.1038)*	0.0314 (0.0134)** *(0.0183)**	0.0239 (0.0096)** *(0.0126)**	0.0749 (0.1272) *(0.1489)*	0.0344 (0.0128)*** *(0.0180)**	0.0248 (0.0093)*** *(0.0121)***	0.5001 (9.4502) *(10.4434)*	0.0372 (0.0121)*** *(0.0163)***	0.0211 (0.0102)** *(0.0108)**
EMN				-0.3781 (0.9759) *(1.1395)*	0.0577 (0.1948) *(0.2269)*	0.3018 (0.1555)* *(0.1692)**	-0.5019 (1.4055) *(1.6554)*	0.0399 (0.1813) *(0.2137)*	0.2899 (0.1518)* *(0.1641)**	-5.8878 (116.8038) *(129.5313)*	0.0378 (0.1533) *(0.1723)*	0.3042 (0.1474)** *(0.1593)**
EGE1				-0.1317 (0.5449) *(0.5273)*	0.0912 (0.1180) *(0.0819)*	0.1705 (0.1015)* *(0.0861)***	-0.2153 (0.8028) *(0.8323)*	0.0957 (0.1102) *(0.0831)*	0.1660 (0.0997)* *(0.0874)**	-2.4249 (49.2962) *(54.5765)*	0.1218 (0.0920) *(0.0742)*	0.1963 (0.0944)** *(0.0934)***
AGE							0.1000 (0.2066) *(0.2464)*	0.0121 (0.0144) *(0.0169)*	0.0127 (0.0105) *(0.0138)*	0.9354 (18.2349) *(20.2553)*	0.0085 (0.0126) *(0.0150)*	0.0119 (0.0101) *(0.0126)*
LFSTOCK										36.9702 (726.0782) *(800.2190)*	0.0195 (0.6375) *(0.7831)*	-0.1129 (0.7628) *(0.8953)*
ECACRA												
UNEM												
INACTIVE												
ECACRF												

	REGRESSION 5			REGRESSION 6			REGRESSION 7					
	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermined	(c) x_{it} endogenous			
$IGE1_{i,t-1}$	0.6263 (0.1278)*** (0.1423)***	0.4689 (0.1113)*** (0.1382)***	0.5554 (0.1392)*** (0.1788)***	0.7371 (0.1434)*** (0.1626)***	0.3899 (0.0977)*** (0.1225)***	0.4300 (0.1255)*** (0.1537)***	0.7274 (0.1365)*** (0.1499)***	0.5741 (0.1072)*** (0.1369)***	0.4963 (0.1341)*** (0.1656)***			
IMN_{it}	0.0163 (0.0040)*** (0.0047)***	0.0054 (0.0062) (0.0074)	0.0075 (0.0077) (0.0096)	0.0168 (0.0043)*** (0.0049)***	0.0127 (0.0056)** (0.0060)**	0.0138 (0.0071)* (0.0076)*	0.0157 (0.0042)*** (0.0048)***	0.0095 (0.0058) (0.0063)	0.0109 (0.0071) (0.0081)			
$IMN_{i,t-1}$	-0.0106 (0.0045)** (0.0056)*	0.0016 (0.0062) (0.0081)	-0.0037 (0.0076) (0.0108)	-0.0130 (0.0048)*** (0.0060)**	-0.0042 (0.0054) (0.0059)	-0.0083 (0.0070) (0.0080)	-0.0128 (0.0047)*** (0.0055)**	-0.0021 (0.0055) (0.0062)	-0.0050 (0.0069) (0.0076)			
EMN_{it}	0.0780 (0.0520) (0.0563)	0.0277 (0.0751) (0.0979)	0.0391 (0.0899) (0.1158)	0.0851 (0.0548) (0.0541)	0.0866 (0.0654) (0.0697)	0.1129 (0.0841) (0.0960)	0.0865 (0.0539) (0.0533)	0.0312 (0.0669) (0.0618)	-0.0036 (0.0846) (0.0849)			
$EMN_{i,t-1}$	-0.1182 (0.0473)** (0.0534)**	-0.0978 (0.0513)* (0.0503)*	-0.1689 (0.0679)** (0.0810)**	-0.1214 (0.0504)** (0.0560)**	-0.1057 (0.0486)** (0.0474)**	-0.1273 (0.0628)** (0.0676)*	-0.1267 (0.0498)** (0.0588)**	-0.0900 (0.0506)* (0.0508)*	-0.1188 (0.0635)* (0.0739)			
$EGE1_{it}$	0.0456 (0.0318) (0.0269)*	0.0765 (0.0448)* (0.0527)	0.0504 (0.0618) (0.0590)	0.0511 (0.0337) (0.0287)*	0.0702 (0.0404)* (0.0406)*	0.0439 (0.0559) (0.0526)	0.0525 (0.0331) (0.0272)*	0.0524 (0.0424) (0.0369)	0.0016 (0.0578) (0.0601)			
$EGE1_{i,t-1}$	-0.0655 (0.0317)** (0.0263)**	-0.0659 (0.0351)* (0.0282)**	-0.1297 (0.0537)** (0.0520)**	-0.0664 (0.0336)** (0.0282)**	-0.0429 (0.0319) (0.0205)**	-0.0587 (0.0464) (0.0388)	-0.0715 (0.0332)** (0.0300)**	-0.0511 (0.0342) (0.0252)**	-0.0592 (0.0470) (0.0480)			
AGE_{it}	0.0080 (0.0049)* (0.0057)	0.0013 (0.0050) (0.0061)	0.0027 (0.0055) (0.0070)	0.0083 (0.0051) (0.0055)	0.0050 (0.0046) (0.0053)	0.0088 (0.0054) (0.0068)	0.0108 (0.0053)** (0.0056)*	0.0080 (0.0055) (0.0062)	0.0113 (0.0063)* (0.0075)			
$AGE_{i,t-1}$	-0.0011 (0.0030) (0.0036)	-0.0070 (0.0027)** (0.0032)**	-0.0033 (0.0031) (0.0035)	-0.0021 (0.0032) (0.0036)	-0.0059 (0.0026)** (0.0031)*	-0.0005 (0.0031) (0.0035)	-0.0022 (0.0032) (0.0037)	-0.0071 (0.0029)** (0.0035)**	-0.0030 (0.0032) (0.0035)			
$LFSTOCK_{it}$												
$LFSTOCK_{i,t-1}$												
$ECACRA_{it}$	-0.0078 (0.0022)*** (0.0021)***	-0.0051 (0.0035) (0.0036)	-0.0072 (0.0042)* (0.0039)*									
$ECACRA_{i,t-1}$	-0.0046 (0.0023)** (0.0021)**	-0.0067 (0.0032)** (0.0032)**	-0.0082 (0.0046)* (0.0050)									
$UNEM_{it}$				-0.0865 (0.2213) (0.1836)	0.1723 (0.3225) (0.3195)	0.2386 (0.3890) (0.3674)						
$UNEM_{i,t-1}$				-0.3702 (0.2206)* (0.2556)	0.2074 (0.2431) (0.2703)	0.8445 (0.3645)** (0.2979)***						
$INACTIVE_{it}$							-0.4672 (0.1766)*** (0.2104)**	-0.6287 (0.3249)* (0.3580)*	-0.8120 (0.4393)* (0.5851)			
$INACTIVE_{i,t-1}$							0.0567 (0.1394) (0.1236)	0.2356 (0.1733) (0.1577)	-0.3325 (0.3420) (0.3591)			

$ECACRF_{it}$				-0.0048 (0.0020)** _(0.0020)**_	-0.0043 (0.0026) _(0.0025)*_	-0.0066 (0.0034)** _(0.0032)**_	-0.0053 (0.0019)*** _(0.0021)**_	-0.0062 (0.0033)* _(0.0029)**_	-0.0132 (0.0047)*** _(0.0051)**_			
$ECACRF_{i,t-1}$				-0.0056 (0.0021)*** _(0.0020)***_	-0.0059 (0.0026)** _(0.0030)**_	-0.0033 (0.0040) _(0.0043)_	-0.0052 (0.0020)** _(0.0019)***_	-0.0036 (0.0028) _(0.0030)_	-0.0062 (0.0041) _(0.0044)_			
OBS.	325			325			325					
SARGAN TEST (p-value)	9.12 (0.4264)	58.44 (0.0378)	27.06 (0.3527)	8.71 (0.4644)	86.75 (0.0007)	36.89 (0.1491)	7.32 (0.6041)	64.35 (0.0696)	32.70 (0.2899)			
AR(1) TEST (p-value)	-4.93 (0.0000) _-3.51_ _(0.0005)_	-4.79 (0.0000) _-3.36_ _(0.0008)_	-4.09 (0.0000) _-2.92_ _(0.0035)_	-5.03 (0.0000) _-3.56_ _(0.0004)_	-4.93 (0.0000) _-3.22_ _(0.0013)_	-4.02 (0.0001) _-3.01_ _(0.0026)_	-5.20 (0.0000) _-3.79_ _(0.0002)_	-5.28 (0.0000) _-3.44_ _(0.0006)_	-2.99 (0.0028) _-2.31_ _(0.0210)_			
AR(2) TEST (p-value)	-0.87 (0.3866) _-0.50_ _(0.6168)_	-1.46 (0.1441) _-0.77_ _(0.4422)_	-1.36 (0.1723) _-0.76_ _(0.4443)_	-0.67 (0.5056) _-0.40_ _(0.6876)_	-1.66 (0.0960) _-0.92_ _(0.3583)_	-1.82 (0.0692) _-1.15_ _(0.2493)_	-0.65 (0.5181) _-0.39_ _(0.6996)_	-0.75 (0.4558) _-0.43_ _(0.6705)_	-1.36 (0.1752) _-0.95_ _(0.3415)_			
Long-run parameters												
IMN	0.0151 (0.0124) _(0.0133)_	0.0133 (0.0101) _(0.0099)_	0.0086 (0.0135) _(0.0157)_	0.0144 (0.0187) _(0.0200)_	0.0140 (0.0080)* _(0.0070)**_	0.0097 (0.0103) _(0.0103)_	0.0104 (0.0179) _(0.0201)_	0.0173 (0.0126) _(0.0131)_	0.0118 (0.0115) _(0.0124)_			
EMN	-0.1077 (0.1761) _(0.2117)_	-0.1321 (0.1340) _(0.1844)_	-0.2919 (0.2186) _(0.2773)_	-0.1380 (0.2748) _(0.3289)_	-0.0312 (0.1025) _(0.1304)_	-0.0252 (0.1437) _(0.1815)_	-0.1475 (0.2644) _(0.3172)_	-0.1382 (0.1610) _(0.1864)_	-0.2431 (0.1802) _(0.2386)_			
EGE1	-0.0531 (0.1159) _(0.1206)_	0.0199 (0.0831) _(0.0964)_	-0.1783 (0.1534) _(0.1612)_	-0.0581 (0.1769) _(0.1908)_	0.0447 (0.0649) _(0.0750)_	-0.0261 (0.1000) _(0.1073)_	-0.0698 (0.1718) _(0.1833)_	0.0031 (0.0997) _(0.1060)_	-0.1144 (0.1225) _(0.1661)_			
AGE	0.0186 (0.0182) _(0.0238)_	-0.0107 (0.0108) _(0.0132)_	-0.0014 (0.0150) _(0.0200)_	0.0239 (0.0287) _(0.0349)_	-0.0014 (0.0089) _(0.0102)_	0.0147 (0.0121) _(0.0160)_	0.0313 (0.0308) _(0.0355)_	0.0021 (0.0148) _(0.0176)_	0.0165 (0.0151) _(0.0192)_			
LFSTOCK												
ECACRA	-0.0332 (0.0119)*** _(0.0145)**_	-0.0223 (0.0071)*** _(0.0085)***_	-0.0345 (0.0108)*** _(0.0123)***_									
UNEM				-1.7372 (1.8359) _(2.1020)_	0.6224 (0.6127) _(0.7629)_	1.9000 (0.9162)** _(0.8548)**_						
INACTIVE							-1.5061 (1.2721) _(1.4377)_	-0.9230 (0.9194) _(1.0003)_	-2.2723 (1.2988)* _(1.7279)_			
ECACRF				-0.0396 (0.0226)* _(0.0285)_	-0.0168 (0.0052)*** _(0.0062)***_	-0.0175 (0.0074)** _(0.0072)**_	-0.0383 (0.0200)* _(0.0247)_	-0.0230 (0.0088)*** _(0.0101)**_	-0.0384 (0.0111)*** _(0.0137)***_			

NOTES: (*), (**), and (***) indicates significance at the 10%, 5% and 1% level, respectively. _(*)_, _(**)_, and _(***)_ denotes the significance of the White (1980) estimator (robust standard errors) at the 10%, 5% and 1% level, respectively. SARGAN TEST is the Sargan test for overidentifying restrictions (Sargan, 1958). AR(1) TEST and AR(2) TEST are the Arellano-Bond test for the first and the second-order autocorrelation in the first differenced residuals, respectively. Time dummies and a constant are included.