Income and Educational Inequalities and Regional Economic Growth in the European Union: the Role of Urbanisation, Geography and Institutions

Thesis submitted for the degree
of Doctor of Philosophy (PhD)

by

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Declaration of Originality

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is my own work. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

This thesis provides an empirical study of how changes in the distributions of income and education affect the evolution of regional economic growth in the EU. It uses microeconomic data from the European Community Household Panel, as well as macroeconomic data from the Eurostat's Regio databases for 102 regions over the period 1995–2002. Income distribution is measured in terms of income per capita and income inequality, not only for the population as a whole but also for those people normally in work; and educational distribution is measured in terms of educational attainment and inequality. Two proxies for educational distribution are considered: the distribution of the education level completed and the distribution of the age at which the highest education level was attained. These data are analysed using exploratory spatial data analysis methods and econometric analyses of static and dynamic panel data models.

The results of the analysis reveal the complexity of the interaction between income and educational inequalities and economic performance in the EU. First, they highlight the positive relationship between income and educational inequality. This relationship is robust to changes in the specification of the model (static or dynamic), in the definition of income and educational distributions and to the inclusion of different control variables, such as population ageing, work access, unemployment and inactivity. This link is related to the higher than expected responsiveness of the EU labour market to differences in qualifications and skills, and to the presence of a level of income inequalities that does not discourage involvement in education. Urbanisation and geography (i.e. latitude), as well as institutional factors, also seem to matter for inequalities. Both income and educational inequalities are lower in social-democratic regimes, in Protestant areas and in regions with Nordic family structures.

Second, the empirical analysis reveals that the increase in a region's inequality in the level of income and the education level completed has a significantly positive — but not causal — relationship with subsequent regional economic growth. The regression results also identify the presence of convergence across European regions, although this is sensitive to the inclusion of control variables. However, when the distribution of age at which the higher education level was completed was considered rather than the level of education attained, the results indicate a negative, but non-robust, association between educational inequality and economic growth. Finally, urbanisation appears to affect regional economic growth, while latitude and institutions, in contrast to what was the case with inequalities, do not matter for growth.

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This thesis is dedicated to my parents and my brother.

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Abbreviations

ECHP:	European Community Household Panel
ESDA:	Exploratory Spatial Data Analysis
EU:	European Union
FEs:	Fixed Effects
FURs:	Functional Urban Regions
GLS:	Generalised Least Squares
GMM:	Generalised Method of Moments
GMM-DIF:	Difference GMM
GMM-SYS:	System GMM
HICPs:	Harmonised Indices of Consumer Prices
IVs:	Instrument Variables
LISA:	Local Indicators of Spatial Association
LM:	Lagrange Multiplier
ML:	Maximum Likelihood
NEG:	New Economic Geography
OBRE:	Optimal B-Robust Estimator
OLS:	Ordinary Least Squares
PPP:	Purchasing Power Parity
REs:	Random Effects

1 Chapter One. Introduction

1.1 Aim, Research Question(s) and Hypotheses

The focal point of this thesis is how *microeconomic changes* in income and in human capital endowment affect the evolution of regional economic growth in the European Union (EU). Microeconomic changes within a region may be examined through changes to the *average* income and education and also through *inequalities* in those areas. The aim of this study is to investigate how income per capita and educational attainment,[1] as well as income and educational inequalities, affect regional economic growth in Europe.

The main research question is:

'Do income and educational inequalities matter for growth?'

This could be phrased in a slightly different way:

'To what extent are income and educational inequalities associated with growth?'

The research question can be decomposed into a number of sub-questions.

- Are income inequalities associated with educational inequalities?
- Are income and educational inequalities affected by common factors, such as population ageing, access to work, unemployment and inactivity?
- Does the exploratory analysis of income and educational inequalities suggest any form of spatial heterogeneity such as an urban-rural divide or an EU north-south divide?
- What is the impact of institutional factors, such as the welfare state, religion and family structure, on inequalities?

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[1] The term 'educational attainment' is used interchangeably with the terms 'educational achievement' and 'human capital stock'.

- Do population ageing, access to work, unemployment and inactivity directly affect regional economic growth or do they have an indirect effect through their impact on inequalities?
- Do urbanisation, geography and institutions shape growth patterns?

The *key concepts* of this study are: regional economic growth, educational attainment, income per capita, income inequalities, educational inequalities and Europe.

I address these questions at the *regional level* for at least four reasons. First, the bibliography that refers to the link between inequalities and growth is limited at the regional level. The empirical investigation of such a link is even more limited. I analyse that relationship at NUTS I or II level due to the availability of the main source of data, the European Community Household Panel (ECHP) dataset (European Commission, 2003). Second, this research question provides new insights not only for regional growth analysis, but also for regional policy analysis. If, for example, income distribution is significantly associated with human capital distribution, the observed relationship between income distribution and regional growth may be governed by the relationship between human capital distribution and growth (Galor and Tsiddon, 1997a: 95). Additionally, the data patterns and anomalies revealed can be used in regional policy. This thesis also illustrates whether more or less egalitarian societies may be good for regional growth and indicate the reasons why government interventions may harm or enhance growth. Third, this research question provides additional material in formulating the convergence and divergence regional economic growth theories. The neoclassical economic growth models (i.e. Solow, 1956; Swan, 1956; Mankiw et al., 1992; Jones, 1997, 1998) not only predict the reduction of territorial income per capita, but also make a long-term forecast of convergence in the distribution of personal income (Benabou, 1996c). Fourth, this study is a preliminary step in the investigation of whether income and human capital growth have disproportionately benefited certain regions of the EU, and whether it is the richer regions that generally benefit much more than the poorer ones (between-region inequality). However, the trend in within-region inequality could affect the trend in between-region inequality, which may reveal σ convergence (Firebaugh 2003). Therefore, the application of this research design draws attention not only to the significance of the within-region inequality for growth, but also to the analysis of the between-region inequality.

I examine income distribution among individuals rather than among households for the following two reasons. First, following the arguments of Kuznets and Gallman (1989), it makes little sense to talk about income inequality among households, because the sizes of the underlying units vary significantly (Peracchi, 2002). Concentrating on individual rather than on household income allows one to abstract that data from changes in patterns of household formation. Second, income and human capital distributions are comparable only when they are measured using the same unit of analysis. Moreover, it is not possible to talk about inequality in the distribution of education among households, because human capital is a form of wealth which is embodied in individuals and not in households; skill and training and this form of wealth arise from 'natural talent' or individual application (Barr 2004).

This research addresses income, not wage, distribution, because as Aghion et al. (1999: 1167) argue

> 'when looking at the effects of inequality on growth, we are primarily interested in the ways in which 'distribution' can affect aggregate output and growth through its impact on individual investments in human or physical capital. What is relevant then is the distribution of wealth, no matter whether this wealth results from the accumulation of labor earnings or capital income'.

Park (1996) suggests four different conceptual rationales of human capital (education): the flow of human capital, the stock of human capital, the rate of return on human capital and the dispersion of human capital.[2] This study focuses on the stock and dispersion (inequality) of human capital, because it investigates whether educational attainment and inequalities affect regional growth. However, the educational attainment of the population is one of the best proxy measures for human capital stock, because it

[2] First, human capital stock refers to the existing levels of human capital in an economy, such as the mean years of schooling of the labour force or the percentage of people at secondary and tertiary education level. It is retained in the local workforce given the characteristics of employment and represents the quality and quantity of the labour force (McNamara et al., 1988). Stock of human capital may be regarded as the primary prediction of human capital endowments. This means that human capital stock is affected by the accumulation of human capital, which in turn is influenced by the rate of return on human capital. For example, according to the neoclassical economic growth models, the stock of human capital will move to those regions offering the highest rates of return. Second, human capital flows are the current level of human capital being produced or added to local human capital stocks. They represent the marginal effect of current human capital investments on the local human capital stock (McNamara et al., 1988) such as enrolment at different levels of education. Third, the rate of return on human capital depicts the marginal productivity of human capital such as the rate of return on education at different levels of education. Fourth, the dispersion of human capital is the variation in the workforce and students over a number of categories such as the dispersion of employed people over the different employment levels (legislators, professionals, clerks, service workers, plant and machine operators etc) or over a range such as the dispersion of educational attainment.

does not look at human capital attributes directly, but rather at the completion of educational levels (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998: 15). Nonetheless, some components of human capital are unmeasured such as the 'specific' human capital and the acquisition of information about the economic system.

This thesis faces many *challenges*. From a theoretical point of view, a challenge is to survey and to attempt to synthesise the various causal hypotheses and mechanisms that have been proposed in the economic, social, political and geographical literature to explain the observed relationships among educational distribution, income distribution and regional economic performance. The literature contributes to the debate over the impact of income and educational inequalities on economic growth. This study empirically contributes to two important research strands within the field of economic growth: educational attainment, income per capita and growth (the first strand); and inequality and growth (the second strand). Hence, a mix of different theoretical models is needed to explain the potential patterns. Notwithstanding the complexity and diversity of existing approaches to regional economic development, the vast majority of them tend to concentrate on macroeconomic variables and processes (Scott and Storper, 2003: 580). This thesis considers both microeconomic (i.e. inequalities) and macroeconomic (i.e. economic growth) variables. A micro-foundation of both human capital endowments and income formation is proposed. Another challenge of this study is that educational distribution is a complex issue and not one that has been researched extensively (Lopez et al., 1998). Who gets educated matters a great deal. This thesis sheds light on that issue. Additionally, it places emphasis on the geographical location which is important in accounting for the economic performance of the regions due to the spatial interactions that take place among them (Ertur and Le Gallo, 2003). The data patterns revealed can be used in regional economic policy. Finally, this thesis places emphasis on the impact of geography, urbanisation and institutions on inequalities and on growth.

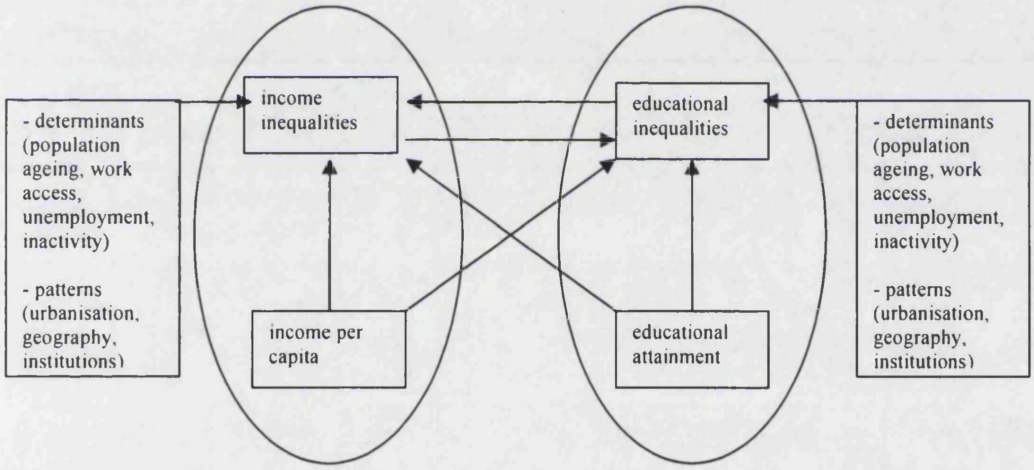
This research is carried out over two steps

1st step: The association between income and educational distribution

The first step of this study is to examine whether income distribution is associated with educational distribution. Since there is plenty of literature on the correlation between income per capita and educational attainment at both national and regional levels, this step is focused on the impact of educational inequalities, educational attainment and income per capita on income inequalities on the one hand, and on the impact of income inequalities, income per capita and educational attainment on educational inequalities on the other (Figure 1.1), while also emphasising the potential patterns.

The first step requires the investigation of the determinants of income and educational inequalities. The level of inequality within a region is a composite of many different forces. Furthermore, the average change of a force may be minimal, because increases in some regions are likely to be offset by declines in other regions. This step is based on the assumption that inequalities in income and human capital are affected by common factors such as population ageing, work access, unemployment and inactivity, because among others both inequalities are proxies for wealth inequalities and reflect the determinants of human behaviour.

Figure 1.1: Association between Income and Educational Distribution



In analysing the causal factors of *income inequality*, my hypotheses are the following.

1. Income inequality is positively affected by *income per capita*, because only a limited number of people can be transferred to higher levels of skills and thus higher wages, while the remainder have to wait their turn (Lydall, 1979). Additionally, intersectoral migration from low added value sectors to those with high added value is not in itself enough to decrease wage inequality.

2. Income inequality is positively affected by *educational attainment*, because although educational expansion in Europe has facilitated numerous favourable opportunities for all individuals, the human capital returns available to rich people are greater than those attained by poorer ones and thus rich people have greater opportunities to engage in higher paid jobs.

3. Income inequality is positively affected by *educational inequality*, due to the responsiveness of the EU labour market to differences in qualifications and skills. The existence of a larger share of highly-educated European workers within a region may signal to employers that those with less education have a lower ability (Wolf, 2004). However, formal education may be seen as an elaborate device for detecting and labelling those who have skills (Spence, 1973 1974; Champernowne and Cowell, 1998).

Although the existing theoretical and empirical literature on *educational inequality* is quite limited, my hypotheses are the following.

1. Educational inequality is positively affected by *income per capita*, because an increase in the income per capita of a region raises the educational opportunities of the highest strata, which implies greater educational inequality. Moreover, the higher the income per capita, the greater the expenditure on private education programmes and the greater the investments in human capital. This, in turn, also implies higher educational inequality.

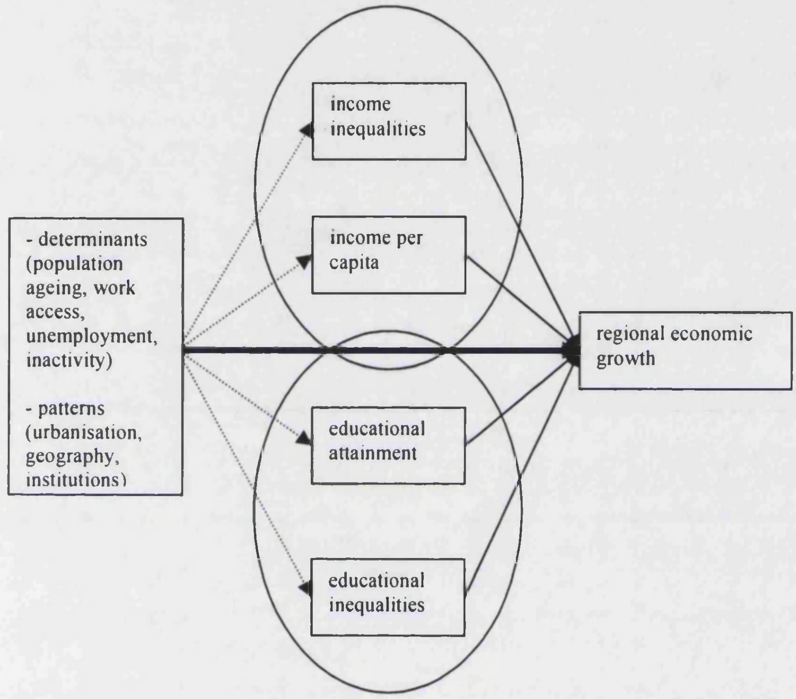
2. Educational inequality is positively affected by *educational attainment*, because the educational opportunities available to different sectors are not equal. State grants are not sufficient to provide educational opportunities to poor people equal to those enjoyed by the rich. Furthermore, the educational opportunities open to poor people are linked not only to their own human capital and socioeconomic background, but also to those of their communities and families ones (Hannum and Buchmann, 2005).

3. Educational inequality is positively affected by *income inequality*, because rich people have better job chances and greater opportunities to progress to a higher, more profitable education level, should it be necessary. Additionally, a further increase in income inequality, for whatever reason, may lead to a self-perpetuating poverty trap that may in turn increase the population share excluded from schooling (Checchi, 2000).

2nd step: To analyse the combined impact of income and educational inequalities on regional economic growth

The second step in this study will be to examine the impact of income and educational distributions on regional economic growth. In this step, the determinants of European regional growth are analysed (Figure 1.2). My intention here is to examine how microeconomic changes in educational attainment and in educational inequality, as well as microeconomic changes in income per capita and in income inequality, affect the evolution of regional economic performance in the EU. Hence, the influence that income and educational distribution can exert on regional economic growth. The determinants of inequalities may affect regional economic growth either directly or indirectly.

Figure 1.2: The Impact of Income and Educational Distribution on Growth



My hypotheses are the following:

1. Regional growth is positively affected by *income inequalities*, because in a *laissez-faire* economy, in which government intervention is minimal, income inequality is fundamentally good for economic (i.e. stipendiary) incentives and therefore should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998).

2. Regional growth is positively affected by *educational inequalities*, because educational inequality is fundamentally good for socioeconomic incentives (i.e. better education) and therefore should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). However, most people require qualifications that are not possessed by everyone. Inequality enables people to increase their investment in human capital by obtaining higher educational qualifications. In addition, the existence of less talented and

educated people imply incentives for those who have achieved such qualifications to seize the higher returns to their skills (Voitchovsky, 2005).

3. Regional growth is negatively affected by *income per capita*, because poor regions grow faster than rich ones, highlighting the convergence process in the EU (Solow, 1956; Swan, 1956; Mankiw et al., 1992; Jones, 1997, 1998).

4. Regional growth is positively affected by *educational attainment*, since education is one of the most powerful instruments known for laying the foundations for sustained growth (Hannum and Buchmann, 2005). Furthermore, the stock of human capital affects the European region's ability to innovate or to catch up with more advanced regions (Nelson et al., 1966). Thus, an increase, for whatever reason, of human capital stock increases the individual's capacity to achieve. This allows individuals to adapt to new technologies and to promote economic growth.

1.2 Research Design

The research design is the means to provide information on the research question(s) in an efficient way that meets the criteria of public accountability, in the sense of openness to public scrutiny (Gaskell, 2003). The research design of the present work is *quantitative analysis*. More specifically, this thesis is an *exploratory analysis*, where innovative techniques are applied to spatial data in order to generate hypotheses about the underlying dynamics of the regional economic system (Rey and Janikas, 2005). It is not a confirmatory analysis, because it does not draw on formal economic theories in order to construct econometric equations, such as β convergence models. Exploratory analysis does not impose any prior restrictive assumption on income, education and regional economic growth distribution. This study also fits into the *classical* statistical framework omitting the use of Bayesian approaches. The focus of attention is on identifying differences across space rather than similarities. It places an emphasis on the role of *spatial effects*. However, the treatment of space in the analysis of income, education and regional growth has received much less attention.

The *research design* can be classified in the following categories:

- *spatial data manipulation and utilities*: data input (sources of data), conversion (i.e. from dbf file to ASCII file) and data output;

- *data transformation*: variable transformation (i.e. merging regions and transforming net personal income from nominal to real) and creation of new variables (i.e. growth variables);
- *initial examination of the transformed datasets*: histograms (i.e. representing the distribution of personal income), boxplots (i.e. identifying outliers and extreme cases), visualisation (i.e. choropleth map) and correlation indices (i.e. the Pearson correlation index);
- *spatial autocorrelation analysis*: spatial weights creation and characteristics (i.e. rook, connectedness, statistical graphics), global and local spatial autocorrelation statistics (i.e. global and local version of Moran's I) and;
- *regression analysis*: static and dynamic regressions (i.e. identifying the mechanisms behind income inequality, educational inequality and regional economic growth).

Briefly speaking, this study starts with simple mapping and geovisualisation, moves on to exploration, spatial autocorrelation analysis and ends with regression analysis.

1.3 Data

The selected methodology depends on the availability of data. This section relates to the analysis of data. It firstly describes the type and sources of the database which define the study area. Then, the benefits and limitations of data and the properties of spatially aggregated data are presented.

1.3.1 Sources of Data and Study Area

The main innovation of this study will be its use of microeconomic data in order to measure intra-regional inequalities in income and human capital endowment. Microeconomic variables will be extracted from the ECHP data survey for the period 1994–2001[3] and will be complemented by macroeconomic variables from the Eurostat

[3] The surveys were conducted regularly at approximately one-year intervals. In these surveys individuals were interviewed about their socioeconomic status, and information was collected about changes to their income changes, job, education status, living space, age, etc. For a review of the ECHP, see the paper by Peracchi (2002).

Regio dataset.[4] The ECHP dataset is based on the 1995 version of NUTS regions and the Eurostat Regio data on the NUTS regions, version 2002. The elaboration process of both databasets is coordinated by Eurostat, making comparisons reliable. However, some adjustment of regions will be required in order to match different datasets (Appendix A1.1).

The availability of the ECHP dataset determines the *study area* over space and time. The time period 1994 was dropped from the sample due to missing data. Unfortunately, there are no data available for the Netherlands. Finnish regions also had to be dropped from the sample because of discrepancies between the regional division included in the ECHP and those in the Regio databank. The resulting database includes 102 NUTS I or II regions from 13 countries in the EU (Table 1.1). On average 116,574 individuals were surveyed, with a maximum of 124,759 in 1997 and a minimum of 105,079 in 2001. Therefore, the choice of the spatial scale of analysis is not based on theoretical considerations, but on data availability.

Table 1.1: European Community Household Panel Data Survey

CODE	COUNTRY	TYPE OF SURVEY	NUTS	NUMBER OF REGIONS
be	Belgium	ECHP	NUTS1	3
dk	Denmark	ECHP	NUTS1	1
de	Germany	SOEP	NUTS1	15
gr	Greece	ECHP	NUTS1	4
es	Spain	ECHP	NUTS1	7
fr	France	ECHP	NUTS1	8
ie	Ireland	ECHP	NUTS1	1
it	Italy	ECHP	NUTS1	11
lu	Luxemburg	PSELL	NUTS1	1
at	Austria	ECHP	NUTS1	3
pt	Portugal	ECHP	NUTS2	5
se	Sweden	ECHP	NUTS2	8
uk	United Kingdom	BHPS	NUTS2	35
Total number of regions				102

Note: SOEP: ECHP based on national survey-SOEP; PSELL: ECHP based on national survey-PSELL; BHPS: ECHP based on national survey-BHPS

1.3.2 The Benefits and Limitations of Panel Data

This study is based on panel data. According to Klevmarken (1989), Hsiao (2003) and Baltagi (2005), the benefits of using panel data are as follows:

1. Panel data control for regional heterogeneity as they suggest that regions are heterogeneous. They are able to control for region- and time-invariant variables. On the contrary, time-series and cross-section studies cannot control the

[4] This type of panel data consists of repeated observations on larger entities, the individual regions (NUTS) of the EU.

heterogeneity, so there is the risk that results obtained may be biased (Moulton, 1986, 1987).

2. Panel data give more informative data and variability, along with a greater degree of freedom and efficiency. The variation in the data can be decomposed into the variation between regions of different sizes and characteristics and the variation within regions. More informative data implies more reliable parameter estimates.

3. Panel data facilitate the study of the dynamics of adjustment. They can be used to estimate, for example, what proportion of income inequality in one period may remain over another period. Therefore, they allow one to estimate intertemporal relations and intergenerational models. However, they do not shed any light on the speed of adjustment to regional economic changes, since the panel is not long enough. In addition, they enable the researcher to construct and test more complex models than purely cross-section or time-series data. For instance, they are able to interact the time-dummies variables with a fixed variable (i.e. urbanisation degree) in order to see how that variable has changed over time. Hence, one is able to identify and measure effects that are not detectable in cross-section or time-series data.

Panel data are not without limitations. The *microeconomic* panel data (ECHP database) involve annual data covering a short time span for each individual, which implies that asymptotic arguments rely crucially on the number of individuals tending to infinity (Baltagi, 2005: 8). On the other hand, increasing the time span of the panel is not without cost due to the amount of non-respondents. Hence, if attrition is a big problem in cross-section studies, it is more serious problem in panels, because subsequent waves of the panel are still subject to non-response (Baltagi, 2005: 8). The rate of attrition increases from one wave to next. Although the country availability increased over time, the overall rate of attrition also increased, since respondents may have died or moved. The major limitation of *macroeconomic* panel data (such as Eurostat's Regio dataset) is that regional economic development is not instantaneous, so that changes in economic development from one year to the next are probably too short term to be really useful (Deaton, 1995). Although the payoff for panel data is over long time periods (i.e. five years), changes in economic development (growth) are calculated every two years, because data cover a short time span for each region.

1.3.3 Spatially Aggregated Data

This study modifies individual data to aggregated data in order to calculate average income and educational attainment, as well as inequalities in those areas, and to relate those variables to macroeconomic variables such as regional economic growth, GDP per capita and public infrastructure. Although the biases resulting from aggregation over individuals may be reduced or eliminated by panel data (Blundell, 1988; Klevmarken, 1989), certain problems are likely to emerge due to the spatial dimension of data.

One problem that has long been identified in the analysis of spatially aggregated data is the 'modifiable areal unit problem' (Openshaw, 1983; Arbia, 1989; Amrhein, 1995). It occurs when arbitrarily defined boundaries are used for measurement. This implies that spatially aggregated data contain a higher degree of uncertainty than the individual components undergoing aggregation and, thus, some observed patterns could be the result of the aggregation level (Fotheringham et al., 2000: 74). Aggregating establishments at any spatial level usually leads to spurious correlations across aggregated variables (Duranton and Overman, 2005). Moreover, the 'modifiable areal unit problem' implies that different results can be obtained from the same statistical analysis at different levels (hence, local, regional or state level) of spatial resolution (Fotheringham et al., 2000: 237). However, Florax and Van der Vlist (2003) have pointed out that straightforward aggregation over space is warranted when the phenomenon to be examined is homogeneously distributed over space (Anselin, 1988a) and the effect of spatial scale on test statistics is pervasive (Griffith et al., 2003). The 'modifiable areal unit problem' typically worsens as higher levels of aggregations are considered, as has been widely recognised by quantitative geographers (Yule and Kendall, 1950; Cressie, 1993). Therefore, the degree of uncertainty with regard to data is higher at national level than at the regional level, and at both levels some observed interactions are eliminated. Accordingly, disparity measures are sensitive to the definition of regions or to the definition of any spatial units (Brülhart and Traeger, 2005: 6) and statistical results are likely to change when the areal units are modified. Nevertheless, spatial analysis cannot completely escape the aggregation biases.

Another characteristic of spatially aggregated data is spatial effects. This term refers to both spatial autocorrelation (spatial dependence) and spatial heterogeneity (non-stationarity). The new theories, such as the New Economic Geography (NEG) models (i.e. Krugman, 1991a, 1991b; Krugman, 1993; Krugman and Venables, 1995, 1996; Puga and Venables, 1996; Martin, 1998; Fujita et al., 1999; Martin, 1999a, 1999b;

Martin, 1999c; Puga, 1999; and Fujita and Thisse, 2002), stress the significance of spatial effects, via, for instance, home market (Krugman, 1980; Helpman and Krugman, 1985; Davis and Weinstein, 2003) and price index (Fujita et al., 1999) effects, and the growing awareness that space matters for regional economic analysis and policy. In neoclassical economic growth models, however, regions are treated as 'isolated islands' (Quah, 1993), because the growth process is a matter of assumptions on the form of the production function and not of interactions across regional economies (Durlauf and Quah, 1999; Fischer and Stirbock, 2006). Geographical location, therefore, is important in accounting for the economic performance of the European regions (Ertur and Le Gallo, 2003).

1. Spatial autocorrelation can be defined as the coincidence of value similarity with location similarity (Anselin, 1988b; Baumont et al., 2003). In other words, it examines whether the data are random or there are similarities between neighbours. For instance, positive spatial autocorrelation means that rich regions tend to be geographically clustered. Another source of autocorrelation is the manner in which some published statistics are produced (Greene, 2003). Spatial dependence has to do with the spatial level of analysis or the geographical scale. Cressie (1993) states that data that are close together in space are more often alike than those that are far apart.[5] Thus, it is possible for spatial autocorrelation to appear at the very local level, but it usually disappears at a larger level, such as national level, due to 'modifiable areal unit problem'. Spatial dependence can also arise from boundary mismatching between the administrative boundaries used to organise the data series (NUTS) and the actual market boundaries over which economic processes operate (Cheshire and Magrini, 2000; Rey and Janikas, 2005; Fischer and Stirbock, 2006). Therefore, if the administrative boundaries do not coincide perfectly with the actual boundaries, then a form of measurement error will introduce spatial autocorrelation into the data (Anselin and Rey, 1991).

2. Spatial heterogeneity means that economic behaviour is not stable over space. It is linked with spatial differentiation. In a regression model, for example, it can be reflected by varying coefficients across regimes (structural instability) or by

[5] Additionally, Cressie (1993) observes that data that are close together in time are more often alike than those that are far apart.

varying error variances across regimes (heteroskedasticity)[6] (Anselin, 1990a, 1990b). A cluster of rich regions (the 'core') is probably distinguished from a cluster of poor regions (the 'periphery') due to spatial heterogeneity (Baumont et al., 2003). A study by Neven and Gouyette (1995), for example, shows that homogeneity is higher among the northern regions of the EU than among the southern ones. Their study suggests the possible existence of different patterns (regimes) in the change in disparities. Anselin (2003c) argues that spatial heterogeneity often occurs concurrently with spatial dependence. Therefore, spatial dependence and spatial heterogeneity may be observationally equivalent (Baumont et al., 2003). For instance, heteroskedasticity is likely to be implied by spatial autocorrelation (Anselin, 1988b; Anselin and Griffith, 1988).

1.4 Methodology: Quantitative Methods

As mentioned above, this study will be conducted using quantitative methods. The methodology is divided into two parts: descriptive analysis and regression analysis of panel data.

1.4.1 Descriptive Analysis: Exploratory Spatial Data Analysis

Descriptive analysis allows us to make sense of the multidimensional micro and macro datasets, to check assumptions and to suggest ways in which research question(s) and hypotheses should be modelled in subsequent stages of the analysis. Therefore, descriptive analysis gives one a feel for how one might best analyse the data. There is increasing recognition of the need to visualise data prior to performing any type of econometric analysis (Fotheringham et al., 2000: 8). Global spatial autocorrelation analysis, for instance, allows one to examine the role of randomness in generated spatial patterns of inequality and growth and to test hypotheses regarding such patterns. Finally, descriptive statistics may tell us something about the theory, without claiming to give the full picture (Overman 2003). Although they are not claimed to reveal a great deal about the theory, they can give an indication of how one might best analyse the data (Fotheringham et al., 2002; Overman, 2003).

[6] It usually arises in cross-section data where the scale of the dependent variable and the explanatory power of the model tend to vary across regions (Greene, 2003).

More specifically, this thesis focuses on Exploratory Spatial Data Analysis (ESDA). ESDA is a set of techniques aimed at visualising and describing spatial distributions (Baumont et al., 2003), such as the distribution of inequality and growth. The exploratory analysis does not impose any prior restrictive assumption on distributions. Thus, the techniques of the exploratory analysis are applied to data in order to generate hypotheses about the underlying dynamics of regional economies. ESDA is a set of techniques aimed at detecting patterns of global and local spatial association and suggesting spatial regimes or other forms of spatial heterogeneity (Haining, 1995; Unwin and Unwin, 1998; Baumont et al., 2003). ESDA highlights the importance of spatial interactions and geographical location in the economic performance of the European regions. However, it is based on the assumption that the value in the region is spread uniformly throughout that region, an assumption which is known as 'ecological fallacy' (Cressie, 1993).

The first (initial) technique of ESDA is to map the data. This allows one to obtain a visual image of them and to identify clusters of similar or dissimilar values. Following Jenk's classification, data are divided into six categories (method of natural breaks).[7]

The second technique of ESDA is the application of boxplots, which is a common but very useful method. The boxplot uses order-based statistics; it clearly shows the median value (the stripe on the box), the first and third quartile (the box), and the largest and smallest values in the dataset (the whiskers) (Fotheringham et al., 2000: 68). Although boxplots tend to emphasise the tails of a distribution, which are the least certain points in the dataset hiding many details of the distribution, they provide some indication of the symmetry of the data and of the presence of bias.[8] Boxplots clearly display the outliers, that are cases with values between 1.5 and 3 box lengths from the upper or lower edge of the box and the extremes that are cases with values of more than 3 box lengths. The outliers and extreme cases play a prominent role in regression analysis and, therefore, they are likely to crucially affect the determinants of inequality and growth. In addition, outliers usually depict 'cores' of clusters. The box length is the interquartile

[7] However, different classification schemes are available, such as 'exogenous' schemes, defined by criteria external to the distribution of data; 'arbitrary' schemes, in which class boundaries are set by arbitrary criteria such as equal intervals; 'ideographic' schemes, where class boundaries are defined by the shape of the distribution, such as the natural breaks and quantiles; and 'serial' schemes that are defined by statistical or mathematical functions (Wright, 2005).

[8] www.netmba.com/statistics/plot/box.

range, which is a measure of spread. A boxplot is a useful way of summarising a set of data measured on an interval scale. It is type of graph which is used to show the shape of the distribution, its central value and variability. The first and third quartiles show the interquartile range. The outliers may present erroneous data.

The third technique of ESDA is spatial autocorrelation analysis. It is likely to reveal relationships in regional data that may otherwise be invisible (i.e. the EU north-south divide). The functionality of the spatial autocorrelation analysis is rounded out by constructing spatial weights (Anselin et al., 2004). Generally speaking, it includes tests for, and visualisation of, both global (test for clustering) and local (test for clusters) statistics (Anselin et al., 2004). Spatial autocorrelation analysis consists of three basic methodological steps.

The first, and the most crucial, step is the construction of spatial weights matrices. One of the main distinguishing characteristics of spatial data analysis is that the spatial arrangement of the regions is taken into account. This is formally expressed in a spatial weights matrix W, with elements w_{ij}, where the ij index corresponds to each region pair (Anselin, 1992: 64). Thus, the first step in the analysis of spatial autocorrelation is to construct the spatial weights that contain information on the 'neighbourhood' structure for each region. Each region is connected to a set of neighbouring regions by means of a spatial pattern introduced exogenously as spatial weights in order to avoid the identification problems raised by Manski (1993).[9]

The two broad ways to create the spatial weights matrix are through the contiguity based spatial weights and the distance band spatial weights. First, the contiguity based spatial weights comprise either rook contiguity that uses only common boundaries to define neighbours or queen contiguity that includes all common points (boundaries and vertices) in the definition (Anselin, 2003a, 2003b). These weights need not to be limited to first order contiguity weights, but higher order weights can also be constructed (Anselin and Smirnov. 1996; Anselin, 2003a, 2003b). Second, the distance band spatial weights can be derived from the distance between points (i.e. X, Y coordinates) computing the minimum distance required to assure that each region has at least one neighbour. However, these weights often lead to a very unbalanced connectedness

[9] For instance, if the spatial weights matrix contains the exogenous or endogenous variables used in the regression models, the empirical model is highly non-linear (Abreu et al., 2004).

structure, especially when the spatial units have very different areas, such as the European regions at different NUTS levels. This is because smaller regions have many neighbours, while the larger ones may have very few or none, yielding unconnected observations or 'islands' (Anselin, 2003a, 2003b). An alternative to distance band spatial weights consists of considering the k-nearest neighbours, choosing the number of neighbours. Hence the critical cut-off for each European region may be expressed as a fixed distance or as a fixed number of neighbours.[10] It is clear that the 'modifiable areal unit problem' is the basis for the introduction of any spatial weights matrix, because a specific level (NUTS) of spatial aggregation has to be chosen as well as a spatial arrangement in terms of patterns of contiguity or distance (Florax and Rey, 1995). Therefore, the specific geographical configuration of the European regions will have some bearing on the choice of the spatial weights matrix (Ertur and Le Gallo, 2003).

In this research, three different spatial weights are considered, because the appropriate choice of the spatial weights is one of the most difficult and controversial issues in ESDA and in spatial econometrics (Anselin, 1988b; Florax and Rey, 1995; Anselin and Bera, 1998; Ertur and Le Gallo, 2003). One advantage of ESDA is that spatial relationships are summarised in spatial weights matrices (Abreu et al., 2004) and thus externalities, among other aspects, are summarised in these matrices. The specific geographical configuration of the European regions and the choice of the scale of analysis (NUTS I or II) will indeed have some bearing on the choice of the weights matrix (Ertur and Le Gallo, 2003). Furthermore, the drawbacks of a specific spatial weights matrix are likely to be the advantages of another. The three different spatial weights schemes considered were as follows:

1. The *rook first order contiguity* spatial weights matrix: It is constructed in order to reduce the effect of the unbalanced connectedness structure of the European regions.

2. The *3-nearest neighbours* spatial weights matrix: The main advantage of this matrix is that it connects a number of 'islands' such as Sicilia and Sardinia to continental Europe. Additionally, the southern United Kingdom is connected to

[10] Other, less favoured, spatial weights schemes are the distance measured by some non-spatial matrices (Gibbons, 2003), as well as schemes which are derived from graph-theoretic concepts such as Gabriel graphs (Bivand and Portnov, 2004).

France and parts of Greece to Italy. However, the European regions are not very closely connected and compact. Two relevant empirical studies in this area are the works of López-Bazo et al. (1999) and Ertur and Le Gallo (2003).

3. The *threshold distance* spatial weights matrix: The minimum distance required to assume that each region has at least one neighbour is relatively long, because Açores and Madeira are situated far from continental Europe. Nevertheless, one advantage of these spatial weights is that there are no unconnected observations.

A major problem in the construction of critical cut-off spatial weights occurs when many values are missing, since every region must be connected to every other via the spatial weights matrix.[11] For instance, increasing the number of nearest neighbours implies that more regions are affected by the missing observations of the nearest neighbours. Another important consideration is that there must be a limit to the range of spatial dependence by the spatial weights matrix (Abreu et al., 2004).

The second step is the global spatial autocorrelation analysis. It is not always obvious whether a variable x is unevenly distributed over space just by looking at a map. If I want to know how strong the spatial association is between neighbouring places, I need some statistical measures. There are a number of simple univariate indicators which allow us to test, in a statistical sense, for unevenness in the spatial distribution of x, such as the geographical distribution of income per capita. The most well-known index is Moran's contiguity ratio or simply Moran's I (Moran, 1950).[12]

$$I = \frac{Cov(x_i, m_i(x))}{Var(x_i)} ,$$

where $m_i(x) = \sum_j w_{ij} x_j$ and w_{ij} is the weight given to region j in the neighborhood average for region i.[13] Each matrix is row-standardised so that it displays relative and not absolute distance. The non-zero elements of the weights matrix reveal the potential

[11] Although the method of 'interpolation' could make predictions for the missing values (Stein. 1999), it is not suggested because of the missing national data.

[12] Other relevant statistical measures of global spatial association are the Getis and Ord statistic (Getis and Ord, 1992, 1993) and the rank adjastency statistic (Ekwaru and Walter, 2001).

[13] Using matrix notation $I = \frac{\tilde{x}' W \tilde{x}}{\tilde{x}' \tilde{x}}$ where $\tilde{x}$ is the mean value of x.

spatial interaction between two regions (Anselin, 1992: 64). Moran's I describes an average trend in the way that a variable x is distributed over space. It is a test for global spatial autocorrelation (Cliff and Ord, 1981). The inference for Moran's I statistic is based on the permutation approach. This is carried out by permuting 999 times the observed values over all locations and by recomputing Moran's I for each new sample. Although several statistics for spatial correlation were developed, the Moran's I test statistic remains an important focus of investigation (Anselin et al., 2004). Hence, the second step in the spatial autocorrelation analysis is to calculate the Moran's I statistic of a variable and its visualisation in the form of a univariate or bivariate Moran scatter plot (Anselin, 1995a, 1995b, 2003c).[14]

The third step is the local spatial autocorrelation analysis. This step makes spatial autocorrelation a problem of local analysis. Fotheringham et al. (2000) stress that the focus of attention in local analysis is on testing for the presence of differences across regions rather than on assuming that such differences do not exist. Those differences exist for many reasons, such as the random sampling variations or the misspecification of reality (Fotheringham et al., 2000). The most well-known index for measuring local relationships in univariate data is the local variant of Moran's I (Anselin, 1995a).[15] The localised version of Moran's I is:

$$I_i = \frac{x_i m_i(x)}{Var(x_i)},$$

which is known as Local Indicator of Spatial Association (LISA). This index can be used to identify spatial outliers, defined as zones having very different values of an

[14] In a univariate Moran scatter plot, the variables are standardised (their mean is zero and variance one) so that the units in the graph correspond to standard deviations. The four quadrants in any Moran scatter plot provide a classification of four types of spatial autocorrelation: high-high (upper right) and low-low (lower left), for positive spatial autocorrelation; high-low (lower right) and low-high (upper left), for negative spatial autocorrelation (Anselin, 2003a, 2003b). The slope of the regression line corresponds to Moran's I. To assess the significance of Moran's I statistic against a null hypothesis of no spatial autocorrelation, a 999 permutation procedure is used. The plots depict income patterns of local spatial association and spatial instability (observations which lie on the horizontal axis are 'islands'). A bivariate measure of spatial correlation relates the value of a variable in a given location to that of a different variable in neighbouring locations (Anselin, 2003a, 2003b). This is useful for the analysis of space-time correlation, where the two variables are the same, but measured at two points in time (Anselin, 2003a, 2003b). Both variables are also standardised. One particularly interesting exercise is to compare the spatial autocorrelation of a variable to its space-time correlation.

[15] Another alternative measure of local relationships in univariate data is the local variant of the global statistic that it is suggested by Getis and Ord (1992; 1993). However, this statistic does not belong to LISA class, because the overall statistic is not equal to the (scaled) sum of the local statistics (Florax and Van der Vlist, 2003: 237).

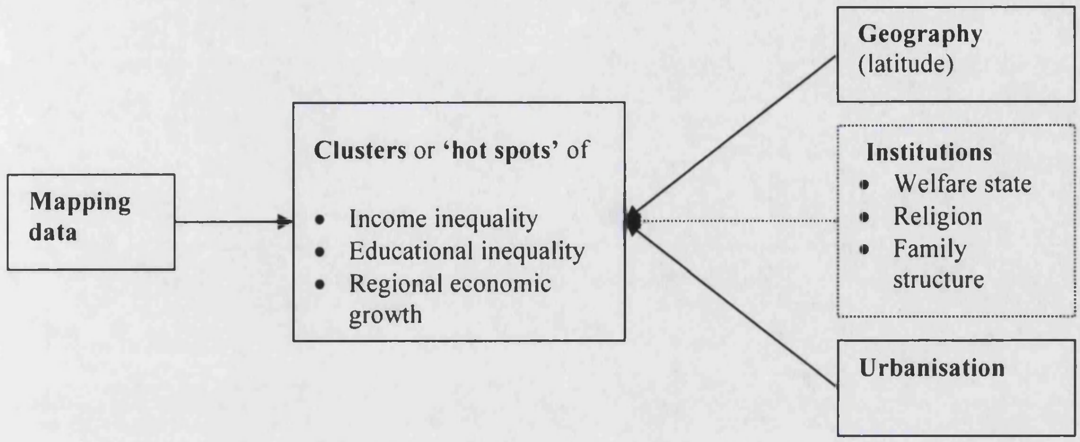
attribute from their neighbours (Fotheringham et al., 2002: 99). It indicates spatial clustering of similar values around the observations (Anselin, 1995a). In other words, it yields a measure of spatial autocorrelation for each individual region. The results are illustrated in a cluster map. The cluster map, which is a special choropleth map, shows those European regions with a significant local Moran statistic classified by the type of spatial correlation generated. The high-high (high surrounded by high) and low-low (low surrounded by low) regions suggest clustering of similar values (positive spatial autocorrelation), whereas the high-low and low-high locations indicate clustering of dissimilar values (negative spatial autocorrelation). The cluster itself consists of the core as well as the neighbours. Anselin (2003a; 2003b) strongly recommends a sensitivity analysis before interpreting the results of LISA maps. More specifically, a 999 permutation procedure at the 0.05 significance level (p-value) is chosen in order to provide stability of the results (Anselin, 1995a).[16]

Then, the Pearson correlation coefficient is used as a measure of linear association. In the correlation analysis, there is no distinction between the dependent and explanatory variables, while both variables are assumed to be random (Gujarati, 2003).

Finally, ESDA is likely to suggest spatial regimes or other forms of spatial heterogeneity (Haining, 1995; Baumont et al., 2003). It enables one to investigate the underlying factors behind income inequality, educational inequality and regional economic growth. In mapping the data, it is possible to establish links between clusters (or 'hot spots') and the underpinning factors such as urbanisation, geography (latitude) and institutions (welfare state, religion and family structure). A cluster (or spatial club) is a group of regional economies that interact more with one another than with those outside the cluster (Fischer and Stirbock, 2006).

[16] The tighter significance criterion eliminates some regions from the map.

Figure 1.3: Spatial Regimes



Economic theory provides no information on the number of regimes or on the way in which foundation factors determine the different clusters of agglomeration (Durlauf and Johnson, 1995). However, the methodology examines three factors (Figure 1.3).

1. *Urbanisation*: The aim with this variable is to explain differences between highly agglomerated urban regions and rural (and usually peripheral) regions.[17]

2. *Geographical variables such as latitude*: The aim with this variable is to investigate differences between the southern and the northern regions of Europe.

3. *Some institutional variables such as the welfare state, religion and family structure*: The aim with these variables is to investigate whether inequalities and growth evolve differently across institutions. However, the detection of this spatial regime is likely to be vague due to many categories.

To sum up:

> 'ESDA should be considered as a first descriptive step before suggesting factors to explain the spatial patterns highlighted and before estimating and testing more sophisticated econometric models' (Ertur and Le Gallo, 2003: 86).

1.4.2 Econometric Analysis

The broad scope of *econometric analysis* can be seen from the following quotation.

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[17] For instance, Bräuninger and Niebuhr (2005) use a partition of EU regions into spatial categories, which are based on a typology of settlement structure established by the Study Programme of European Spatial Planning.

> '...econometrics may be defined as the quantitative analysis of actual economic phenomena based on the concurrent development of theory and observation, related by appropriate methods of inference' (Samuelson et al., 1954).[18]

The underlying empirical strategies used in the econometric analysis of income, human capital and economic growth patterns are presented. The calibration of econometric models provides information on the determinants of the patterns through the estimates of the model's parameters. The econometric models give empirical content to the hypotheses.

This study considers the *non-spatial econometric literature,* which has focused on models of absolute location (Abreu et al., 2004). The notion of spatial heterogeneity addressed here is broader than the one typically used in the spatial econometrics literature, which has concentrated on models of relative location (or spatial dependence) and is tightly linked to the concept of spatial regimes. Following the argument of Abreu et al. (2004), while spatial regimes are an extreme form of spatial heterogeneity, incorporating spatial variables such as urbanisation, latitude, the welfare state, religion and family structure directly into the regression also takes account of spatial heterogeneity, albeit on a more gradual and refined scale. Although studies on relative location do not apply sophisticated econometric techniques to account for spatial effects, the non-spatial econometric literature can gain insights from conducting ESDA, because it reveals variables that might otherwise be invisible.

This study uses *linear regression analysis*. The econometric models deal only with cases where the number of regions is large relative to the number of years. It is simpler to treat the smaller set (time-effect) as an ordinary set of variables. Thus, the econometric model is a one-way error component regression model. Additionally, econometric analysis provides a robust and non-robust testing ground for hypotheses about the underlying mechanisms behind inequality and growth. Concerning the causal impact, there is difficulty in distinguishing, for instance, the effects of inequality on growth from the effects of growth on inequality, and the possibility that other factors are the cause of both inequality and growth.

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[18] Cited in Gujarati (2003: 1)

In the regression models, an inference about an individual is made using aggregate data for a region due to 'ecological fallacy' (Cressie, 1993). Therefore, the regression models depend on individual, group and regional specific characteristics.

The selection of the determinants of income inequality, educational inequality and regional economic growth are based not only on the theoretical background but also on the availability of datasets. As the available regional datasets have not included a satisfactory range of time-series (1995–2002), I use pooled time-series — cross-section (panel) analysis. The complexity of the relationships will possibly dictate causality, heteroscedasticity and autocorrelation tests (Wooldridge, 2002; Greene, 2003; Gujarati, 2003; Hsiao, 2003; Baltagi, 2005). I also prefer the panel analysis rather than the cross-section alternative because there are two potential econometric problems with cross-section regression: the measurement error (in income inequality and in educational variables) and the omitted variable bias.

This study uses two methods of panel regression analysis: *static models* and *dynamic models*. These models are increasingly popular for panel data analysis among regional science researchers. With repeated observations for 102 regions, panel analysis permits us to study the dynamics of change within short time-series. The combination of time-series with cross-regions can enhance the quality and quantity of data in ways that would be impossible using only one of those two dimensions (Gujarati, 2003). The static models endow regression analysis with both a spatial and temporal dimension. The first dimension pertains to a set of cross-regional units of observation, while the second pertains to periodic observations of a set of variables characterising those cross-regional units over a particular time span. There are several types of static panel data analytic models. The static methods of panel estimation presented here are the pooled ordinary least squares (OLS), fixed effects (FEs) and random effects (REs) models. These models are the most widely used in panel regression analysis. They allow one to use the pooled regression model as the baseline for comparison. As the surveys of the ECHP dataset were conducted regularly at approximately one-year intervals, the error terms of inequality regressions are expected to be correlated with the regional specific effect. This problem can be dealt with using the FEs models, in which the error terms may be correlated with the regional specific effects. Nevertheless, according to Yaffee (2003), the FEs models are not without their drawbacks. These models frequently have too many cross-sectional units of observation, requiring too many dummy variables for their specification. Too many dummy variables may sap the model of a sufficient degree of freedom to conduct adequately powerful statistical tests. He also notes that a model with many such variables may be plagued with multicollinearity, which increases the standard errors and thereby drains the model of the statistical power to test parameters. If these models contain variables that do not vary within the groups, parameter estimation may be precluded. This study also includes dynamic models due to the short time period of analysis. For instance, the equilibrium may be constrained in the short-run because of supply rigidities or factor immobilities that are removed in the longer-run (Combes et al., 2005). The dynamic models test for the existence of autocorrelation. Finally, using the dynamic models, I can obtain both short-run and long-run parameters.

More specifically, the econometric analysis in this study starts with a static panel data model of the form

$$y_{it} = \beta' x_{it} + v_i + \varepsilon_{it}$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...T$). y_{it} is the dependent variable (income inequality, educational inequality or regional economic growth), x_{it} is a vector of explanatory variables, β is the coefficient, v_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 known as the composite error.

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

$$y_{it} = \beta' x_{it} + \eta' d_{\lambda i} + v_i + \varepsilon_{it},$$

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, I introduce $m-1$ dummy variables (categories). Category d_{1i} is referred to as the base category. Comparisons are made with that category (Gujarati, 2003).

This static model is characterised by one source of persistence over time, due to the presence of unobserved regional specific effects. As mentioned earlier, the static methods of panel estimation used are the OLS, FEs and REs methods. To evaluate which technique is optimal, it is necessary to consider the relationship between the regional specific effects and the regressors, among others. First, in the event that there are neither significant regional nor significant temporal effects, I pool all of the data and run an OLS regression model. Although for the most part there are either regional or temporal effects present, there are occasions when neither of these is statistically significant. In other words, the pooled OLS estimator assumes that the unobserved regional specific effect is uncorrelated with the explanatory variables and that each region is independent and identically distributed, ignoring the panel structure of the data and the information they provide (Johnston and Dinardo, 1997). The resulting bias in pooled OLS is caused by omitting a time-constant variable and is sometimes called the heterogeneity bias (Wooldridge, 2003: 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 the unobserved heterogeneity to be correlated with the explanatory variables (Wooldridge, 2003: 440). The FEs estimator is obtained by removing the unobserved regional characteristics, which are a potential source of bias. More specifically, it is a pooled OLS estimator that is based on the time-demeaned variables. The FEs estimator also requires that there be within-group variation in variables for at least some groups. I therefore introduce a year dummy variable with the degree of urbanisation (time-constant variable) in order to see whether the effect of urbanisation has changed over the period 1995–2000. Third, the REs estimator assumes that the regional specific effects are uncorrelated with all of the explanatory variables in all time periods. The efficient estimator of the REs model provided 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 the 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. The usual diagnostic tests are also 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 the OLS model. The LM test is a test for regional effects. Large values for the LM statistic favour the REs model.

In the static models, I assume that the regression disturbances are homoskedastic, with the same variance across time and regions. However, heteroskedasticity 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 covariance matrix is presented following the White estimator for unspecified heteroskedasticity (White, 1980).

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

$$y_{it} = \delta y_{i,t-1} + \beta' x_{it} + \zeta' x_{i,t-1} + \gamma' z_i + v_i + \varepsilon_{it}$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...T$). y_{it} is the dependent variable (income inequality or educational inequality), $y_{i,t-1}$ is the (first) lagged dependent variable, x_{it} is a vector of explanatory variables, $x_{i,t-1}$ is a vector of (first) lagged independent variables, δ, β and γ are coefficients, a is an intercept, v_i are the random 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 v_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 the econometric model contains a lagged endogenous variable (Baltagi, 2005).

The dynamic panel structure of my 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, 2003; Wooldridge, 2003; Baltagi, 2005). Arellano and Bond first transform the model to eliminate the regional specific effect (v_i). The observed urbanisation ratio (z_i) is eliminated as well. The first-differencing transformation is:

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

where all variables are expressed as deviations from period means. Models in first differences usually encounter 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 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 the model, I assume that the explanatory variables might be:

- strictly exogenous, if $E[x_{it}\varepsilon_{is}]=0$ for all t and s,
- 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
- 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 population ageing 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.[19] Additionally, Arellano and Bond (1991) developed Sargan's test (Sargan, 1958) for over-identifying restrictions. The Sargan test has an asymptotic chi-squared distribution in the case of the homoskedastic error term only. Both the homoskedastic one-step and the robust one-step GMM estimators are presented. The two-step standard error model

[19] 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: 282).

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 stressed that treating variables as predetermined or endogenous increases the size of the instrument matrix very quickly. This implies that GMM estimators with too many overidentifying restrictions may perform poorly in small samples (Kiviet, 1995).

As mentioned above, the dynamic model is 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 that variable, whereas the long-run effect is the effect obtained after full adjustment of the dependent variable. The short-run effect of the variable x is β and its long-run effect is $\beta + \zeta / 1 - \delta$. Long-run standard errors are calculated using the Delta method (Greene, 2003).

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

1.5 The Structure of the Present Study

The next chapter presents the main theoretical background of this study. It investigates statements by drawing on evidence from studies in economics, sociology, political science and geography. The determinants of income and educational inequalities have been examined in numerous studies using a variety of different approaches. This paper aims to develop the understanding of inequalities within the context of regional science. Chapter 2, then, gathers together knowledge from diverse disciplines and promotes interdisciplinary research on the impact of inequalities in income and education inequalities on regional economic growth.

Chapters 3 and 4 explore and analyse the European income and educational distributions, respectively. The core methodology of these chapters is ESDA. The focus of attention is on identifying income and educational differences across space, rather than similarities. These chapters examine whether income and educational externalities, among other things, spill over the barriers of regional economies, indicating the existence of spatial dependence, and whether the probability of neighbouring economies sharing similar urban, geographical (such as latitude) and institutional (such as welfare state, religion and family structure) conditions is relatively high, indicating the existence of spatial heterogeneity. I examine whether the geographical distributions of the

European regions exhibit any patterns of income and educational polarisation. Chapters 3 and 4 also highlight the within-region inequalities in income and education as components of the European income and educational distributions, respectively.

Chapter 5 compares European income and educational distributions through the parametric models of lognormal and gamma distributions, cross-tabulation analysis and the within-region component. This chapter also examines whether spatial interactions and geographical location are important in regional growth issues. It goes on to explore the possibility of a persistent polarisation pattern among regions.

Chapter 6 explores the determinants of income and educational inequalities in the regions of the EU. More specifically, it examines not only how microeconomic changes in income distributions affect educational inequalities, but also how microeconomic changes in educational distributions affect income inequalities. The methodology of this chapter is econometric analysis, which deals with the estimation of both static and dynamic models. A number of alternative specifications are tested in order to evaluate the robustness of the results and the impact of population ageing, work access, unemployment and inactivity on inequalities. This chapter provides an empirical framework for understanding the differences in income and educational inequalities in the EU and testing whether they correspond to differences in urbanisation, geography and institutions.

Chapter 7 deals with the main research question of this study. It examines whether and to what extent income and educational inequalities are associated with growth. The methodology of this chapter is econometric analysis. Similar to the previous chapter, it tests the robustness of the results to the inclusion of additional variables in the model specification such as population ageing, work access, unemployment and inactivity. Finally, it explores the role of urbanisation, geography and institutions in the regional economic growth process.

The final chapter summarises the main points of the inquiry, synthesises the empirical results, draws some policy implications for regional economic policy and discusses directions for future research.

Appendix A1

Appendix A1.1: Regions: Code and Name

	MICRO-DATA (based on NUTS, version 1995)		MACRO-DATA (based on NUTS, version 2002)	
NUTS (version 1995)	CODE	NAME	CODE	NAME
NUTS0	be	Belgium	Be	Belgium
NUTS1	be1	Région Bruxelles-capitale/Brussels hoofdstad gewest	be1	Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest
NUTS1	be2	Vlaams Gewest	be2	Vlaams Gewest
NUTS1	be3	Région Wallonne	be3	Région Wallonne
NUTS0-NUTS1	dk	Denmark	Dk	Denmark
NUTS0	de	Federal Republic of Germany (including ex-GDR from 1991)	De	Germany (including ex-GDR from 1991)
NUTS1	de1	Baden-Württemberg	de1	Baden-Württemberg
NUTS1	de2	Bayern	de2	Bayern
NUTS1	de3	Berlin	de3	Berlin
NUTS1	de4	Brandenburg	de4	Brandenburg
NUTS1	de5	Bremen	de5	Bremen
NUTS1	de6	Hamburg	de6	Hamburg
NUTS1	de7	Hessen	de7	Hessen
NUTS1	de8	Mecklenburg-Vorpommern	de8	Mecklenburg-Vorpommern
NUTS1	de9	Niedersachsen	de9	Niedersachsen
NUTS1	dea	Nordrhein-Westfalen	Dea	Nordrhein-Westfalen
NUTSNEW	dex	Rheinland-Pfalz+Saarland	Deb	Rheinland-Pfalz
			Dec	Saarland
NUTS1	ded	Sachsen	Ded	Sachsen
NUTS1	dee	Sachsen-Anhalt	Dee	Sachsen-Anhalt
NUTS1	def	Schleswig-Holstein	Def	Schleswig-Holstein
NUTS1	deg	Thüringen	Deg	Thüringen
NUTS0	gr	Greece	Gr	Greece
NUTS1	gr1	Voreia Ellada	gr1	Voreia Ellada
NUTS1	gr2	Kentriki Ellada	gr2	Kentriki Ellada
NUTS1	gr3	Attiki	gr3	Attiki
NUTS1	gr4	Nisia Aigaiou, Kriti	gr4	Nisia Aigaiou, Kriti
NUTS0	es	Spain	Es	Spain
NUTS1	es1	Noroeste	es1	Noroeste
NUTS1	es2	Noreste	es2	Noreste
NUTS1	es3	Comunidad de Madrid	es3	Comunidad de Madrid
NUTS1	es4	Centro (ES)	es4	Centro (ES)
NUTS1	es5	Este	es5	Este
NUTS1	es6	Sur	es6	Sur
NUTS1	es7	Canarias (ES)	es7	Canarias (ES)
NUTS0	fr	France	Fr	France
NUTS1	fr1	Île de France	fr1	Île de France
NUTS1	fr2	Bassin Parisien	fr2	Bassin Parisien
NUTS1	fr3	Nord - Pas-de-Calais	fr3	Nord - Pas-de-Calais
NUTS1	fr4	Est	fr4	Est
NUTS1	fr5	Ouest	fr5	Ouest
NUTS1	fr6	Sud-Ouest	fr6	Sud-Ouest
NUTS1	fr7	Centre-Est	fr7	Centre-Est
NUTS1	fr8	Méditerranée	fr8	Méditerranée
NUTS0-NUTS1	ie	Ireland	Ie	Ireland
NUTS0	it	Italy	It	Italy

NUTS1	it1	Nord Ovest	itc1	Piemonte
			itc2	Valle d'Aosta/Vallée d'Aoste
			itc3	Liguria
NUTS1	it2	Lombardia	itc4	Lombardia
NUTS1	it3	Nord Est	itd1	Provincia Autonoma Bolzano-Bozen
			itd2	Provincia Autonoma Trento
			itd3	Veneto
			itd4	Friuli-Venezia Giulia
NUTS1	it4	Emilia-Romagna	itd5	Emilia-Romagna
NUTS1	it5	Centro (I)	ite1	Toscana
			ite2	Umbria
			ite3	Marche
NUTS1	it6	Lazio	ite4	Lazio
NUTS1	it7	Abruzzo-Molise	itf1	Abruzzo
			itf2	Molise
NUTS1	it8	Campania	itf3	Campania
NUTS1	it9	Sud	itf4	Puglia
			itf5	Basilicata
			itf6	Calabria
NUTS1	ita	Sicilia	itg1	Sicilia
NUTS1	itb	Sardegna	itg2	Sardegna
NUTS0-NUTS1	lu	Luxembourg	Lu	Luxembourg (Grand-Duché)
NUTS0	at	Austria	At	Austria
NUTS1	at1	Ostösterreich	at1	Ostösterreich
NUTS1	at2	Südösterreich	at2	Südösterreich
NUTS1	at3	Westösterreich	at3	Westösterreich
NUTS0	pt	Portugal	Pt	Portugal
NUTS2	pt11	Norte	pt11	Norte
NUTS2	pt12	Centro (PT)	pt16	Centro (PT)
NUTS2	pt13	Lisboa e Vale do Tejo	pt17	Lisboa
NUTS2	pt14	Alentejo	pt18	Alentejo
NUTS2	pt15	Algarve	pt15	Algarve
NUTS2	pt2	Açores (PT)	pt2	Região Autónoma dos Açores (PT)
NUTS2	pt3	Madeira (PT)	pt3	Região Autónoma da Madeira (PT)
NUTS0	se	Sweden	Se	Sweden
NUTS2	se01	Stockholm	se01	Stockholm
NUTS2	se02	Östra Mellansverige	se02	Östra Mellansverige
NUTS2	se04	Sydsverige	se04	Sydsverige
NUTS2	se06	Norra Mellansverige	se06	Norra Mellansverige
NUTS2	se07	Mellersta Norrland	se07	Mellersta Norrland
NUTS2	se08	Övre Norrland	se08	Övre Norrland
NUTS2	se03	Småland med öarna	se09	Småland med öarna
NUTS2	se05	Västsverige	se0a	Västsverige
NUTS0	uk	United Kingdom	Uk	United Kingdom
NUTS2	uk11	Cleveland, Durham	ukc1	Tees Valley and Durham
NUTS2	uk13	Northumberland, Tyne and Wear	ukc2	Northumberland, Tyne and Wear
NUTS2	uk12	Cumbria	ukd1	Cumbria
NUTS2	uk81	Cheshire	ukd2	Cheshire
NUTS2	uk82	Greater Manchester	ukd3	Greater Manchester
NUTS2	uk83	Lancashire	ukd4	Lancashire
NUTS2	uk84	Merseyside	ukd5	Merseyside
NUTS2	uk21	Humberside	uke1	East Riding and North Lincolnshire
NUTS2	uk22	North Yorkshire	uke2	North Yorkshire
NUTS2	uk23	South Yorkshire	uke3	South Yorkshire
NUTS2	uk24	West Yorkshire	uke4	West Yorkshire
NUTS2	uk31	Derbyshire, Nottinghamshire	ukf1	Derbyshire and Nottinghamshire
NUTS2	uk32	Leicestershire, Northamptonshire	ukf2	Leicestershire, Rutland and Northants

NUTS2	uk33	Lincolnshire	ukf3	Lincolnshire
NUTS2	uk71	Hereford and Worcester, Warwickshire	ukg1	Herefordshire, Worcestershire and Warks
NUTS2	uk72	Shropshire, Staffordshire	ukg2	Shropshire and Staffordshire
NUTS2	uk73	West Midlands (County)	ukg3	West Midlands
NUTS2	uk40	East Anglia	ukh1	East Anglia
NUTS2	uk51	Bedfordshire, Hertfordshire	ukh2	Bedfordshire, Hertfordshire
NUTS2	uk54	Essex	ukh3	Essex
NUTS2	uk55	Greater London	Uki	London
NUTS2	uk52	Berkshire, Buckinghamshire, Oxfordshire	ukj1	Berkshire, Bucks and Oxfordshire
NUTS2	uk53	Surrey, East-West Sussex	ukj2	Surrey, East and West Sussex
NUTS2	uk56	Hampshire, Isle of Wight	ukj3	Hampshire and Isle of Wight
NUTS2	uk57	Kent	ukj4	Kent
NUTS2	uk61	Avon, Gloucestershire, Wiltshire	ukk1	Gloucestershire, Wiltshire and North Somerset
NUTS2	uk63	Dorset, Somerset	ukk2	Dorset and Somerset
NUTS2	uk62	Cornwall, Devon	ukk3	Cornwall and Isles of Scilly
			ukk4	Devon
NUTS2	uk92	Gwent, Mid-South-West Glamorgan	ukl1	West Wales and The Valleys
NUTS2	uk91	Clwyd, Dyfed, Gwynedd, Powys	ukl2	East Wales
NUTS2	uka4	Grampian	Ukm1	North Eastern Scotland
NUTS2	uka1	Borders-Central-Fife-Lothian-Tayside	Ukm2	Eastern Scotland
NUTS2	uka2	Dumfries and Galloway, Strathclyde	Ukm3	South Western Scotland

2 Chapter Two. Literature Review: Income and Educational Inequality and Regional Economic Growth

2.1 Introduction

Inequalities are significant in regional economic analysis. This chapter examines cases of income and educational inequalities. The current belief is that these inequalities are almost perfectly correlated and affect regional economic progress. A challenge in regional economic growth literature is to survey and to attempt to synthesise the various causal hypotheses and mechanisms that have been proposed in the social science literature — particularly by economists — to explain the observed relationships between income inequality, educational inequality and regional economic performance. Although there is a large amount of literature on the subject (Saint-Paul and Verdier, 1993; Aghion et al., 1999; Benabou, 2000; Checchi, 2000; Benabou, 2002; Thorbecke and Charumilind, 2002; Galor and Moav, 2004), this chapter will not examine all the relevant theories and arguments in great detail. Instead, it concentrates on the central issue of the microeconomic foundation of regional economic growth; that is, whether income and educational inequalities affect growth. Put differently, a great challenge is whether more or less egalitarian societies are conducive to growth.

This chapter seeks to contribute to the debate over the role of income and educational inequalities in regional economic growth. There are several channels through which inequalities influence regional economic performance. This chapter attempts to cross disciplinary boundaries within economic, social, political, psychological and geographical fields. The first step is to investigate any association between income and educational distribution, measured in terms of average levels and inequality therein. The second step is to analyse the impact of inequalities on growth.

This chapter is structured as follows. Section 2.2 analyses the concepts of human capital, the income level of an economy[20] and regional growth. Sections 2.3 and 2.4 outline the determinants by which people's income and education level are

[20] Hereafter, I use 'economy' to refer to countries, regions or states.

differentiated from one another. They consider the extent to which income distribution correlates with educational distribution. Both sections examine the determinants of social polarisation,[21] known as between-group inequalities. They shed light on the investigation of whether illiterate people and poor people are synonymous. More specifically, Section 2.3 presents the determinants of income inequality. It describes the impact of income per capita, educational attainment and educational inequality on income inequality. Section 2.4 presents the determinants of educational inequality. It reviews the impact of educational attainment, income per capita and income inequality on educational inequality. Sections 2.5 and 2.6 examine the impact of income and educational inequality, respectively, on growth. The last section offers some conclusions.

2.2 Defining Education, Income and Regional Growth

Concepts are common points of reference used to group phenomena that are otherwise differentiated geographically and linguistically (Rose, 1991: 447). Without concepts, information about different regions may be assembled together, yet there is no basis upon which to relate one region to another (Rose 1991: 447). Bearing in mind that concepts are chosen depending upon the purpose of the research (Sartori, 1984), this section looks at the concepts of education, income and regional growth.

Education (human capital) is a multidimensional concept. It has been defined by the Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development (1998: 9) as '*the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity*'. A number of economists have adopted the broad concept of human capital, including the work of Adam Smith in the eighteenth century. The pioneering work of Schultz (1959; 1961a; 1961b; 1962; 1963) views human beings as types of capital and investment. He treats human resources as a form of capital. People who invest themselves extend the range of

[21] Social polarisation may be described as the 'extreme case' (high value) of social stratification. However, what does 'social stratification' mean? According to Parsons (1949: 166) social stratification concerns ' *the differential ranking of the human individuals who compose a given social system and their treatment as superior and inferior relative to one another in certain socially important respects*'. Social stratification, and hence social polarisation, depends on ranking, which is considered a truly fundamental phenomenon of socioeconomic systems. In quantitative variables ranking is objective, while in qualitative variables the selection of a moral evaluation as the central criterion of the social rank involved in polarisation might be considered arbitrary (Parsons, 1949). In this research, since quantitative analysis is used in the measurement of both income and education , moral evaluations are not involved.

choice that is available to them, enhance their welfare and, subsequently, the welfare of their society.

Schultz (1961a) has classified human activities using five major dimensions. The first dimension is that of formally organised education at the elementary, secondary and tertiary levels. The cost of this type of human capital consists of the costs of the services of teachers, librarians and administrators. It also includes the costs of maintaining and operating the educational plant and the income foregone by students. The second dimension is the on-the-job training organised by firms. It differs from formal education in that investment is made within the workplace rather than in an institution that specialises in teaching (Becker, 1962: 11). The cost of this training is usually borne by employers and depends on the type of training and on the demand for different skills. The aim of such training programmes is to adjust the education of workers to the demand for new skills and abilities. Training is regarded as an important aspect of labour market flexibility. A lack of mobility, for instance, may inhibit the scope for firms to bring about changes in work practice and organisational structures (De Serres, 2003; OECD, 2003). Less-educated workers and those working on a part-time basis are much less likely to receive training, especially when employed by a small firm (De Serres, 2003: 14). On the other hand, Wolf (2002: 251) has argued that vocational training has been used as a panacea for the disadvantaged and the unemployed for many years. The third dimension is the study programmes for adults that are not organised by firms, such as the extension programmes in agriculture that contribute to transmitting new knowledge and to developing skills among farmers. Nowadays, people quite often spend some of their leisure time in improving their skills and knowledge. The fourth dimension is the migration of individuals and families to adjust to changing job opportunities. The movement of people from one sector to another changes their overall welfare. The fifth dimension of human capital is that of health facilities and services. This concept includes all expenditures that affect life expectancy, strength and stamina, and the vitality of people, among others.

Economists, sociologists and geographers have extended the concept of human capital to many other areas. According to Becker (1962), an additional dimension of human capital concerns the acquisition of information about the economic system. Generally speaking, the economic system influences the efficiency, allocation and distribution of human resources. People can reduce the risk of their investment if they have a better knowledge of the market. Spence (1973; 1974) supports the notion that education may act as a 'signal' because of imperfect information which may generate temporary educational mismatch. For instance, the coexistence of a high incidence of overeducation among school-leavers and a lack of work experience reflects the educational mismatch (Hartog, 2000). This type of mismatch conceptually differs from the skill mismatch that is the actual mismatch between acquired and required skills (Allen and van der Velden, 2001). Hence, the acquisition of information about the economic system influences not only the distribution of human beings, but also the educational and skill mismatch.

Benporath (1980) places emphasis on another dimension of human capital, the personal or 'specific' human capital created by investments in reputation and personal relationships, which is known as the F-connection (families, friends and firms). He argues that families, friends and firms play a major role in the allocation and distribution of human resources. Similarly, Becker (1962), Becker and Tomes (1986) and Becker and Barro (1988) have extended human capital to encompass marriage, fertility and family relations. For example, the learning of children is closely related to their parental human capital. Closely related to 'specific' human capital is the concept of social capital (Coleman, 1988; Coleman, 1990; Bourdieu, 1993; Putnam, 1993; Fukuyama, 1995; Putnam, 1995). However, social capital is generally understood to be a matter of relationships rather than the property of individuals (Schuller, 2000). Thus, human capital focuses on the economic behaviour of individuals, while social capital on networks, norms and trust. Social capital contributes significantly to the formation of human capital, since family and community support may have a greater pay-off than investment in buildings and teacher's salaries (Fedderke et al., 1999; Inkeles, 2000).

The significance of, and emphasis on, the above human capital dimensions varies in the existing literature. Becker (1964), for example, argues that formal education, informal education within the family and on-the-job training are the most important investments made in human capital. Denison (1962), on the other hand, places an emphasis on the advancement of knowledge and technical progress.[22] Arrow (1962) highlights the economic implications of learning-by-doing. He states that the concept of learning-by-doing differs from the concept of formal education in the sense that learning is the

[22] Denison (1962) argues that the contribution of schooling to growth and to income differentials is an issue of 'ability bias' (Griliches, 1997). For this reason human capital is usually the residual factor in many economic growth equations.

product of experience; it can only take place through the attempt to solve a problem and therefore takes place during activity.

A significant characteristic of all the above dimensions of human capital is spillovers. They may occur via investments in education and on-the-job training (i.e. the gains that accrue to other producers from observing and imitating their successful counterparts), and via investments in health (i.e. when one person invests in his/her health, he is less likely to make other people ill due to a contagious disease) (Abler, 2005). Spillovers may also occur through social relations and within families from generation to generation. For example, Loury (1981: 843) has argued that the allocation of training and education resources among any generation of young people depends upon the income and human capital distribution among their parents. An individual's level of human capital is an increasing function of the parental level of human capital.

The multidimensional concept of education is governed by the criterion of optimisation subject to the constraints that are specific to the circumstances and surroundings pertaining to each individual (Schultz, 1975: 827). People usually reallocate their resources in response to changes in socioeconomic conditions, formal education, on-the-job training, social capital and any other form of human capital.

The investment in human capital differs substantially among countries, regions, cities and persons. Younger persons, for example, change jobs more frequently than older ones. More talented individuals are expected to receive more opportunities for educational and on-the-job training programmes than less-educated ones. Furthermore, the cost of education varies across space, because each location has a different production function, without taking into account the differences in natural resource endowments.

Income is a more straightforward concept than that of human capital. First of all, income is a 'pure' quantitative concept, while the concept of human capital is more likely to be a 'derived' quantitative concept (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998). Income, like human capital, may differ among countries, regions, cities and persons. For example, the main source of personal income among students and younger persons is payments from their parents or unemployment and redundancy benefits. The main source of income of workers is wages and salaries, while the income of older people usually comes from pensions. Income levels differ across space because wages, salaries and pensions differ according to location. For instance, the main source of income in rural areas might be the income from self-employment or farming. Even if one takes into account the same source of personal income, the income levels may differ across space, since the underlying determinants may also differ. Kalleberg and Lincoln (1988), for instance, have found evidence of cross-country differences in income inequalities. The earnings of US employees are conditioned by job characteristics, positions in the authority hierarchy and union representation, while the earnings of Japanese employees are shaped by age and organisational structures.

The most widely acknowledged broad categories of *regional growth* are regional income growth (the 'micro-approach' to growth) and regional economic growth (the 'macro-approach' to growth). Generally speaking, regional economic growth is a broader concept than growth in regional income, because the macroeconomic concept takes into account externalities to physical and human capital (Temple, 1999), and inseparable public policies such as public infrastructure policies. Moreover, the concept of regional economic growth encompasses the overall growth effect of a policy outcome, like inflation or the budget deficit (Temple, 1999: 121). Nevertheless, both regional income and economic growth differ across space.

On analysing the concepts of human capital, income and economic growth, it is clear that they are closely associated with one another. Economist, sociologists and geographers have detected numerous signs that improvements made at the individual level are among the major sources of economic growth. Furthermore, the structure of income is primarily determined by investment in schooling, on-the-job training and investment in migration (Schultz, 1962). Becker (1962) argues that an examination of investment in human capital may be useful in understanding income inequality. Human capital investment activities are associated with other types of investment activities such as investment in physical capital or in the real estate market. Those activities also contribute to regional economic growth. Some of those activities have lagged effects on others. For instance, human capital activities have a greater influence on future real income than on present income levels.

2.3 The Impact of Income Per Capita, Educational Attainment and Educational Inequality on Income Inequality

There is a vast body of 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 education levels and inequality in that area, on income inequality is perceived by the literature. To achieve that aim, I will first review the link between income and inequality, before going on to analyse the impact of educational attainment and inequality on income inequality. The dynamic structure of inequalities is also considered.

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, 2003). Additionally, income levels are often perpetuated from one generation to another by means of inheritance, cultural background and, more generally, the characteristics of the community (Bourguignon and Morrisson, 1990; Cooper et al., 1994; Durlauf, 1996; Checchi, 2000). This allows for intergenerational stability in income, indicating the existence of a positive autocorrelation in inequalities. Cooper (1998), for instance, has pointed out that families from the poorer or more wealthy communities tend to exhibit a greater degree of 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 the same level of income for more than one generation. Income persistence is often viewed (as in Lane, 1971) as an essential characteristic in rewarding achievement and, particularly, in ensuring that the most suitable people are allocated the most suitable roles. The presence of inequalities in income provides an additional incentive for 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: 14). According to Aghion and Bolton (1992) and Galor and Zeira (1993), the persistence of income inequalities across generations is possible only if capital markets are imperfect. High intergenerational correlations imply less mobility in the distribution of income. The key 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). *Income per capita* was found to have an inverted U-curve effect on income inequality (Kuznets, 1955). Income inequality increases as nations begin to industrialise and, then, declines at later stages of industrialisation. This relationship is known as 'Kuznets curve' and was formalised later by Knight (1976a; 1976b), Robinson (1976) and Fields (1979). The Kuznets curve shows that in the early stages of industrialisation, the labour force is primarily engaged in agriculture. As industrialisation takes hold, workers move from the larger agricultural sector to the smaller industrial one and, since wages are usually higher in the industrial sector, this migration boosts further income inequality (Firebaugh, 2003). Therefore, at first income distribution becomes more unequal as income increases. At a highly advanced stage of economic development, income inequality and income per capita are negatively related. More explicitly, according to the neoclassical economic theory, as the agricultural sector shrinks and the industrial sector increases in size, further movement from the agricultural sector to the industrial sector serves to reduce, rather than increase, income inequality. Therefore, development is inegalitarian in the early stages of development and becomes more egalitarian during subsequent stages.

The key factors underlying the inverted U-curve effect of income per capita on inequality are industrialisation and labour migration. The additional factors behind this association include market and government failures, government social expenditures and the development of financial services. For example, De Gregorio and Lee (2002) show that income inequalities are negatively correlated with government social expenditure. Schultz (1962) indicated that modifications in income transfers and in progressive taxation are relatively weak factors in altering the distribution of income. Motonishi (2000; 2006) argues that the effect of financial service development on income inequalities is not straightforward. On the one hand, more developed financial services enable the poor to borrow from the rich and this leads to a decrease in income inequality; while on the other hand, the new financial services are often notavailable to the poor due to constraints on the credit market arising from information asymmetries. Finally, market failures, such as credit constraints and monopsony or monopoly power and government failures, often increase income inequalities (Graham, 2002).

Despite the significant amount of the research that has set out to test the Kuznets curve at the national level, the results are ambiguous (i.e. Ahluwalia, 1976; Papanek and Kyn, 1986; Anand and Kanbur, 1993; Bourguignon and Morrisson, 1998; Checchi, 2000; Motonishi, 2006). Ahluwalia (1976), for instance, finds for a cross-section of counties evidence to support the inverted U-curve, while Anand and Kanbur (1993) 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 per capita income, since social structures, such as historical heritage, religion, ethnic composition and cultural traditions, evolve quite differently across countries (Checchi, 2000). In this thesis, I do not expect to test the validity of the Kuznets curve for two reasons. Firstly, the majority of the relevant empirical studies focus not only on European but also on less economically advanced countries (i.e. African countries). Secondly, the studies in question show that the declining segment of the Kuznets curve begins around 1970 (Nielsen and Alderson, 1997). However, I 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. I therefore expect to find that over the period 1995–2000 income per capita had a negative effect on income inequality.

The notion of *education* as an underlying factor in income differences also has a long history, dating back to the work of Adam Smith (Griliches, 1997). Based on the work of Schultz (1961a; 1962; 1963), Becker (1962; 1964) and Mincer (1958; 1962; 1974), income inequality is generally considered to be affected by educational attainment, in a process which is sometimes referred to as 'skills deepening' (Williamson, 1991). A higher level of educational attainment is achieved through improvements in access to education (i.e. lower tuition fees, better education financing, improved vocational training), a higher quality of education (i.e. better services from teachers, librarians and administrators) and greater investment in physical capital for education. Improved access to education, for example, is likely to increase the earning opportunity of the lowest strata, leading to a reduction in earning inequality (Checchi, 2000)[23]. Furthermore, more widespread access to education allows for a more informed participation in the market economy, reducing the lobbying ability of the rich, while simultaneously increasing the social and job opportunities of the poor, implying lower inequality. According to a statement from the World Bank statement, education is one of the most powerful instruments known for reducing income inequality (World Bank, 2002). Education, in addition, facilitates numerous favourable changes for individuals, because it reflects abilities, choices and preferences (Hannum and Buchmann, 2005).

[23] Income inequality, at least in industrialised countries, is explained by a rise in earning inequality (Gottschalk and Smeeding, 1997; Cornia et al., 2001). Hence inequality in pay is definitely an important component of total income inequality (Blinder, 1974; Brown, 1977).

Educational achievement is not only process of increasing credentials, but it is also an instrument that leads to a higher level of aspiration, with people tending to be more informed and therefore gaining specific traits which are likely to increase productivity. Increasing in educational attainment raise the individual's occupational outcomes and subsequent economic status. For example, the elimination of tuition fees means that a wider population are more likely to obtain degrees and enrol in graduate school. Recent studies by Eicher and Garcia-Penalosa (2001), De Gregorio and Lee (2002) and Heshmati (2004) demonstrate how higher levels of educational attainment contribute towards making income distribution more equal.

According to Knight and Sabot (1983), the impact of educational attainment on income inequalities depends on the balance between the 'composition' and the 'wage compression' effect. 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, over time education tends to decreased income inequality. An increase in the level of education reduces the wages of highly-educated workers, because their supply goes up, and simultaneously raises the wages of the less-educated workers, because their supply goes down. Thus, an increase in the educated labour supply is likely to increase competition for positions requiring advanced educational credentials and thereby should reduce the income differential between the educated and uneducated people (Tinbergen, 1975; Lecaillon, 1984). Moreover, an increased proportion of the population attaining a higher level of education leads to inflation in the value of educational credentials and in the long run to decreasing wages for highly-educated workers. Thus, the effect of education on income inequality is based on a balance of supply and demand.

The effect of educational attainment on income inequality also depends on the type of education. Glomm and Ravikumar (1992) claim that public education reduces income inequality more quickly than private education. Cardak (1999) extends the work of Glomm and Ravikumar (1992) and shows, first, that heterogeneous preferences increase income inequality and second, public education can compensate for the added heterogeneity and reduce income inequality. The promotion of public education causes the distribution of income to become less skewed, because although the revenues of the poor are taxed, they enjoy the benefits of the public education system. Hence one way to decrease income inequality is through increased support for public education.

Spence's (1973; 1974; 1976) signalling model offers a different perspective on the relationship between income and education. This model demonstrates 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 for more educated people has little to do with academic and vocational skills, because formal education is seen as an elaborate device for detecting and labelling those who have skills (Champernowne and Cowell, 1998; Wolf, 2004). The individual's education level is more closely related to innate ability and to 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). Differences in educational attainment may arise as a consequence of heterogeneity in ability. Galor and Tsiddon (1997b) and Hassler and Mora (2000), for example, support the idea that individuals with a higher level of innate cognitive ability can fare better with less knowledge than others do. They state that talented individuals are also more productive and opt for a higher rate of technological growth. For them, genetic characteristics are highly correlated with the education that children receive and their skills. In contrast, López et al. (1998) support the notion that education levels are not necessarily correlated with abilities. 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 *educational inequality* are positively correlated (Jacobs, 1985; Glomm and Ravikumar, 1992; Saint-Paul and Verdier, 1993; Galor and Tsiddon, 1997a; Chakraborty and Das, 2005). More explicitly, Thorbecke and Charumilind (2002: 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 employers that those with less education have less ability, and hence the latter's earnings may be reduced accordingly, which may also lead to a greater wage inequality between workers with high and low levels of education. 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.

Taking into consideration Bowles' (1972) statement, more equal levels of education could lead to significantly greater equality of economic opportunity and incomes without challenging the European institutions and without requiring any major redistribution of capital. Human capital inequalities may be a significant cause of occupational disparities across social groups and therefore a cause of income inequalities. Since education offers economic opportunities to both advantaged and disadvantaged groups, the poor but talented members of society can achieve appropriate positions in the European economy regardless of their social background, thus improving their relative economic standing (Hannum and Buchmann, 2005), while elites can manage to maintain their socioeconomic status by getting more education than the masses (Walters, 2000). Therefore, the positive relationship between income and educational inequality is likely to highlight the responsiveness of the European labour market to differences in qualifications and skills.

Extremely low income individuals might face credit constraints that prevent them from rising to a profitable education level (Dur et al., 2004). They also face constraints if credit markets are imperfect. Hence, due borrowing constraints and imperfect markets, the ability of poorer people to invest in education may depend on their parental wealth.

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

2.4 The Impact of Educational Attainment, Income Per Capita and Income Inequality on Educational Inequality

The distribution of human capital is a complex but little explored issue. Who gets educated is important. This section considers the determinants by which people's investment in human capital are differentiated. It considers the impact of educational attainment and income distribution on educational inequalities, as well as their dynamic structures.

Firstly, educational inequality is determined by its initial value. The cultural reproduction theory (i.e. Bowles and Gintis, 1976), on the one hand, bears testimony to the persistence, and sometimes the increase, of educational inequality in a modern society. The intergenerational transmission of educational achievement is a result of social backgrounds. People's educational opportunities are linked not only to their own human capital, but also to those of their communities and families. The value of an individual's own educational credentials depends in part on how they compare to the credentials of their family and, more generally, those of the local population (Hannum and Buchmann, 2005: 339). For example, students in higher education usually tend to come from relatively favoured backgrounds (Blöndal et al., 2002: 7). Mosteller and Moynihan (1972), Becker and Tomes (1986) and Galor and Tsiddon (1997a) point out that the individual's level of human capital is an increasing function of the parental level of human capital. This is known as the home environment externality. The powerful force exerted by family background on educational inequality is also discussed by Machin and Vignoles (2004). They demonstrate that levels of human capital among the British became more closely connected to parental income and human capital in the 1970 cohort than was the case for the 1958 cohort. Nevertheless, Hauser and Sewell (1986) have found that family background has independent effects not only on schooling but also on ability. On the other hand, the general theory of industrialisation (i.e. Treiman, 1970) argues that the decrease in educational inequality is a result of educational expansion. Educational inequality is a temporal characteristic of industrialisation. The more industrialised a society, the greater the educational expansion. This implies more educational opportunities for the lower strata and, thus, a lowering of human capital inequality (Blau and Duncan, 1967). Empirically, Kikkawa (2004) supports the general theory of industrialisation in Japan and in the United States, showing that the more that education expands, the smaller the effect of social background on educational attainment.

Economic theory and empirical studies yield ambiguous predictions about the likely effects of *educational attainment* on educational inequalities. It has been mentioned that with respect to the general theory of industrialisation, the stock of education negatively affects educational inequality as result of educational expansion, which is an excellent device for a wider diffusion of opportunities and thus economic well-being (Ram, 1990: 266). Educational expansion narrows human capital inequalities within regions by promoting a meritocratic basis for status attainment in which the talented can achieve appropriate positions in the economy, regardless of their social background (Hannum and Buchmann, 2005).[24] However, one critical factor underlying the negative

[24] Walters (2000: 254), however, argues that educational expansion alone does not change the relative position of social groups in the 'education queue', and elites manage to maintain their status by getting more education than the masses. For this reason one needs to consider separately the effects on

relationship between educational attainment and educational inequality is the cost of human capital. Low cost makes education more affordable. A lower cost of education could be achieved through higher grants, subsidised loans, subsidised 'work-study' jobs and other financial devices or through lower tuition fees and a lower interest rate on borrowing for educational purposes. The empirical studies by Londono (1990), Lam and Levison (1991) and Thomas et al. (2001) illustrate that educational inequality is negatively associated with the average years of schooling in a country. Ram (1990) shows that the Kuznets curve in education exists only when standard deviation is used as an inequality measure. He shows that as the human capital stock increases, educational inequality first increases and, after reaching a peak, starts to decline in later phases of educational expansion. Cornia et al. (2001) also test the Kuznets curve in education. Their study finds that in the early stages of economic development, educational expansion increases the number of skilled workers less rapidly than their demand, thus leading to an increase in inequality. As the relative abundance of skilled workers rises, the wage rate of skilled workers declines relative to that of unskilled workers and inequality drops. Most empirical studies show that countries with higher levels of human capital stock are more likely to achieve equality in human capital than those with a lower stock. These studies illustrate that the 'maximum inequality threshold' in education is likely to rise with economic development, as it is with the adoption of skill-intensive technologies. Nevertheless, Ceroni (2001) stresses the positive effects of educational attainment on educational inequality. She argues that if education is privately financed, the poor require relatively higher returns to increased expenditure on education in order to increase the human capital stock. For this reason the poor invest a smaller share of their income in education than the rich do. Moreover, occupations that require high levels of investment in human capital are beyond the reach of poor people, who choose instead to work for others (Banerjee and Newman, 1993).

The overall impact of *income per capita* on educational inequality seems to be negative. More explicitly, the higher the individual income, the higher the expenditure on education for all strata. This identifies education as a key instrument for securing equal opportunities for people and for helping to improve their life chances (Wolf, 2002). An increase in income per capita within a region is likely to increase the income levels of

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educational inequality of an overall increase in educational expansion and changes in educational reforms.

the poor. This raises the educational opportunities for the lowest strata, which implies a lower level of educational inequality. Moreover, the higher the income levels of the rich, the higher the rate of taxation, and thus the greater the expenditure on public education programmes (Saint-Paul and Verdier, 1993), which usually constitute the major portion of the European educational programmes. This will mean more public investment in human capital, and, therefore, increased educational opportunities for the lowest strata, leading to a decline in educational inequalities.

Nevertheless, the level of income within a region depends on the financial, economic market and government shortcomings. The greater the failings, the lower the level of income per capita. These failings limit the opportunities open to the poor and their economic well-being. For example, credit constraints may prevent the poor from undertaking the efficient amount of human capital investment, perpetuating human capital inequalities (Loury, 1981; Benabou, 1996c; Graham, 2002). More explicitly, Graham (2002: 67) argues that due to credit market imperfections, access to capital depends on the wealth that may be offered as collateral, which means that an individual's initial assets (i.e. land, credits, education) may be an important determinant of his/her ability to finance investments with even higher returns. This may cause a particular problem for human capital investments, because future earnings cannot be used as collateral and, since education plays a central role in determining opportunity investments, this market failure has a particularly negative impact in terms of the opportunities for the poor to move out of poverty. Akin to market failure, government failure contributes to the perpetuation of educational inequality. The behaviour of governments and the allocation of public goods reflect the distribution of political power and the organisational capacity of different societal groups (Birdsall and Estelle, 1993; Graham, 2002). Thus, government failure is likely to generate an unequal distribution of political power that can lead to a perpetuation or concentration of income and educational inequality.

The effect of *income inequality* on educational inequality is not unambiguous. On the one hand, Saint-Paul and Verdier (1993) have supported the idea that income inequality has a negative effect on human capital inequality. More explicitly, the greater the income inequality, the higher the rate of taxation and the larger the expenditure on public education programmes. This yields higher public investment in human capital, that in turn implies decreased educational inequality. If income inequality is found to have a negative effect on educational inequality, this is likely to indicate the effectiveness of the European social system, or from a different perspective, the lack of responsiveness of the European labour market to differences in qualifications and skills. On the other hand, Checchi (2000) argues that an increase in income inequality may involve a self-perpetuating poverty trap that may increase educational inequality. The more skewed the income distribution, the larger the share of the population that are excluded from schooling and the greater the inequality in educational achievement. From this perspective, European citizens who live under poverty can only escape that condition by increasing their educational attainment. A positive relationship between income and educational inequality is likely to indicate the responsiveness of the European labour market to differences in qualifications and skills.

Empirically, Jensen and Nielsen (1997) have found some support for the notion that poverty forces households to keep their children out of school. Mayer (2001) examined the effect of growing income inequality on the educational attainment of low-income and high-income children. Her results indicate that inequality has not led to an increase in high school graduation, but may have brought a slight decrease, especially for low-income people, whereas the growth in inequality appears to have led to an increase in college graduation, but only among young people from the top half of the income distribution. Mayer also considers two contrasting economic theories about how income inequality may affect children's educational attainment: effects due to the parents' income and effects due to the consequences of other people's income. Finally, Acemoglu and Pischke (2000) analysed the patterns of college enrolments across the United States. They did not find any evidence to support the idea that college enrolments increase more in states where wage inequality and a return to schooling rise more substantially (Thorbecke and Charumilind, 2002: 1488).

2.5 The Impact of Income Inequality on Regional Economic Growth

A number of economic theories and arguments have been constructed in the quest to find the linkage between income inequality and economic growth. When looking at the effects of inequality on growth, we are primarily interested in the ways in which income distribution can affect aggregate output and growth through its impact on different channels (Aghion et al., 1999), such as incentives, investments in physical and human capital and habits. What are possible transition mechanisms that might link inequality and growth? A number of arguments have been made as to why more or less egalitarian societies can actually be good for growth and why redistribution policies from rich to poor and government interventions may harm or enhance growth. This section primarily presents the arguments that shed light on the inequality-growth relationship.

First of all, the relationship between economic growth and income inequality is determined by *economic incentives*. The operation of the free market in the pursuit of private profit not only provides strong incentives for work, but may also generate inequalities (Champernowne and Cowell, 1998). Many sociologists and economists — going back to Adam Smith — support the idea that inequality is fundamentally good for incentives and therefore should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). Inequality promotes a productive economy by creating incentives and encouraging competition. Free markets provide signals that can help to optimise production, resulting in greater gains, but not necessarily in lower income inequality (Heyns, 2005: 167). Along these lines, Voitchovsky (2005: 276) argues that in an economic structure where ability is rewarded, effort, productivity and risk-taking will also be encouraged, generating higher growth rates and income inequality as a result. To sum up, the greater the income inequality, the stronger the incentive to invest either in physical or in human capital, and thus the higher the growth rate. Barro (2000) states that this is the case only if investments incur high costs in relation to median income that may be only be in the range of very wealthy agents. Incentives appear to stimulate preponderantly production of such goods and services that only the rich can afford to buy, rather than to enable the poor to buy the goods that they most urgently need. Without incentives, entrepreneurial and business activity and risk-taking might cease, capital markets would dry up and economic growth would grind to a halt (Heyns, 2005: 165). Any public policy aimed at reducing income inequality may produce negative incentives for economic efficiency and, therefore, may harm economic growth. Such policies include the taxation system and the public housing policies, among the key devices used to redistribute income (Chang, 1994; Lui, 1997; Chang, 1998). Champernowne and Cowell (1998: 16) demonstrate that strong policies of redistribution may hamper the ability of exceptionally efficient and successful firms and entrepreneurships to expand and attract staff with the best talents by offering them the inducement of unusually high pay. Thus, in a *laissez-faire* economy, in which government intervention is minimal, inequality is fundamentally good for incentives, which, in turn, enhance growth. In contrast to this view, equality is a major tenet of socialism and a primary source of communist legitimation (Austen, 2002; Gijsberts, 2002).

Income inequality can affect growth through *investments in physical and human capital.* Classical economists (i.e. Smith, 1776; Keynes, 1920; Kaldor, 1956, 1957; Lewis, 1961) support the notion that more income inequality favours physical capital accumulation, because the rich agents have a higher marginal propensity to save compared to the poor.[25] This increases aggregate savings,[26] which in turn increases growth rates. Contrary to the classical approach, the modern one (Galor, 2000; Galor and Moav, 2000, 2004) suggests that the relationship between income inequality and growth depends on the stage of economic development (or industrialisation). During the early stages of economic development, physical capital accumulation is the prime engine of economic growth. High initial income inequality stimulates high aggregate saving, which, in turn, increases physical capital accumulation. Physical capital then stimulates the process of economic development. Hence, income inequality enhances economic development by channelling resources towards individuals with a higher propensity to save. The modern approach is similar to the classical one only for the early stages of economic development. At later stages of economic development, human capital accumulation replaces the accumulation of physical capital as the prime engine of growth, due to capital-skill complementarity. During the economic process, the increased availability of physical capital raises the return on investment in human capital. However, due to credit market imperfections (Galor and Zeira, 1993; Benabou, 1994, 1996a, 1996b, 1996c; Durlauf, 1996; Benabou, 2000, 2002), poorer agents may find their access to human capital curtailed.[27] Thus, in sufficiently wealthy economies, equality may stimulate investment in human capital which promotes economic growth, because human capital accumulation is greater if it is shared by a larger segment of the society. In other words, equality promotes growth via investment in human capital, because more individuals are able to invest in human capital (Perotti, 1996; Easterly, 2001); and equality could alleviate the adverse effect of credit market constraints on human capital accumulation (Galor and Moav, 2004). Furthermore, during the process

[25] Most empirical studies support the theory of a positive relationship between inequality and savings (Kelley and Williamson, 1968). Smith (2001), however, has found evidence that income inequality affects savings only in countries with low levels of financial market development.

[26] Dynan et al. (2004) demonstrate that saving rates increase with wealth.

[27] Flug et al. (1998), for example, show that economic volatility — lack of financial markets, income or employment volatility and income inequality — has a negative effect on the accumulation of human capital. Dixit and Pindyck (1993) show that uncertainty also has a negative effect on investment in physical capital. Flug et al. (1998) argue that volatility has a stronger correlation with investment in human capital than with investment in physical capital.

of development, the constraints on the credit market gradually diminish, differences in savings behaviour between rich and poor agents decline and the effect of income inequality on economic growth becomes insignificant (Galor and Moav, 2004: 1021). Nevertheless, Benabou (1994) argues that even minor imperfections in capital markets can lead to a high degree of stratification. Low levels of income inequality facilitate numerous favourable changes for regions, because they offer plenty of economic chances to both advantaged and disadvantaged groups. This allows for a better allocation of resources and more efficiency in physical and human capital investments. For instance, as income inequalities decline, fewer people under-invest in education because of credit market imperfections (Galor and Zeira, 1993; Owen and Weil, 1998; Maoz and Moav, 1999; Benabou, 2000; Galor and Moav, 2000). Finally, taking into consideration only physical capital, Banerjee and Newman (1991; 1993) and Aghion and Bolton (1992; 1997) support the notion that with credit market imperfections, equality positively affects an individual's physical capital investment opportunities. To summarise, the effect of inequality on economic growth depends not only on the region's level of income, but also on the relative returns to physical and human capital.

Income inequality and economic growth are closely interlinked with *habits*. Champernowne and Cowell (1998: 16) argue that once people are accustomed to a degree of comfort they will regard it as a hardship to return to an earlier and lower standard of living. This means that a rapid reduction in income inequality is likely to slow down or even halt economic progress, highlighting the difficulty of the adjustment process.

The relationship between income inequality within a nation and economic growth can also be investigated through *political economy* models such as the voting models (i.e. Perotti, 1992, 1993; Alesina and Perotti, 1994; Aghion et al., 1999), but it is not clear-cut. The basic argument for the negative effect of inequality on growth is that the higher the income inequality, the higher the rate of taxation, the lower the incentive to invest and the lower the growth rate (Bertola, 1993; Alesina and Rodrik, 1994; Persson and Tabellini, 1994). The argument in support of a positive effect, on the other hand, is that the higher the income inequality, the higher the rate of taxation, the larger the expenditure on public education programmes, and thus the higher the public investment in human capital and the higher the growth rate (Aghion and Bolton, 1990; Saint-Paul and Verdier, 1993).[28] Hence, the trade-off between the incentive to invest (which is the fundamental mechanism of a *laissez-faire* economy) and the expenditure on public education programmes (which reflects a fundamental government policy of a command economy) determines the inequality-growth relationship. However, government controls regulate the extent to which individuals might pursue their own self-interest (Begg et al., 2000).

The effect of income inequality within a nation on economic growth also depends upon the effect of *socio-political instability* (i.e. Venieris and Gupta, 1983, 1986; Londregan and Poole, 1990; Mauro, 1995; Alesina et al., 1996; Alesina and Perotti, 1996; Svensson, 1998; Mauro, 2004). However, this channel plays a key role in the inequality-growth relationship of less-developed countries beset by political and social unrest or violence, such as African and Latin America countries and less so for European countries. In a society with considerable income inequality, the gap between the mean income and the potential legal income of low-skilled workers is large, and hence this is likely to give incentives for very poor people to engage in disruptive activities such as crimes against property and crimes of violence (Nilsson, 2004: 3). Additionally, the more unequal the distribution of income, the higher the probability for disruptive activities and protests, and the higher the frequency of government changes. Thus, when the gap between rich and poor widens, the poor may experience a greater temptation to engage in disruptive activities that are usually at the expense of the rich (Benabou, 1996c). The above cases accentuate the negative effect of inequalities on growth.

The empirical research that has been carried out on the effect of income inequality on economic growth is less unambiguous than the theory. The vast majority of the reduced-form estimates find that inequality has a negative effect on growth (i.e. Persson and Tabellini, 1994; Perotti, 1996; Barro, 2000). Less empirical studies support the positive effect of inequality on growth (i.e. Li and Zou, 1999; Forbes, 2000). For instance, Forbes (2000) uses panel estimation and her results suggest that in the short and medium term, an increase in a country's level of income inequality has a significant positive relationship with subsequent economic growth. Her estimates are highly robust across samples, variable definitions and model specifications. Nonetheless, all the above

[28] Nevertheless, Sylwester (2000) stresses that the larger the expenditure on public education programmes, the lower the growth rate.

studies examine the relationship between income inequality within a nation and economic growth.

2.6 The Impact of Educational Inequality on Regional Economic Growth

Economic performance depends increasingly on talent, creativity, knowledge, skills and experiences. In modern economies, those characteristics shape opportunities and rewards (Wolf, 2002: 14). Although educational attainment has gained a central role in economic growth analysis (i.e. Stokey, 1991; Benhabib and Spiegel, 1994; Barro, 2001), the link between educational inequality and economic performance is less straightforward than it may appear. The literature on the influence of educational inequality on economic growth is quite limited. This section analyses the contributions of incentives, technological progress in production and life expectancy to the relationship between educational inequality and growth.

It has been argued that inequality is fundamentally good for *incentives* and therefore should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). Not only income inequality, but also educational inequality, is good for incentives. The greater the educational inequality, the greater the incentive for an individual to attain a higher educational level and to get more academic qualifications and training. However, most people require qualifications that are not possessed by everyone (Wolf, 2002). The existence of less talented and educated people implies incentives to seize the higher returns for ones skills (Voitchovsky, 2005). As Chiswick (1974: 17) says

> 'since human capital is created at a cost, no one would willingly invest in human capital unless it generated sufficient monetary or nonmonetary benefits to compensate for the cost'.

This is likely to enhance economic growth.

Educational inequality also determines growth through *technological progress*. In the early stages of economic development, a wide distribution of human capital might be a necessary condition for take-off. Inequality encourages members of the highly-educated segments of society to increase their investment in human capital, while equality traps the society as a whole at a low level of investment in human capital (Galor and Tsiddon, 1997a: 94). Inequality is essential in order for a region to increase the aggregate level of human capital and output. In addition, economic growth is affected by the percentage of individuals who inherit a large enough amount of wealth to enable them to invest in human capital (Galor and Zeira, 1993: 51) and only rich people are able to do so. The parental level of human capital, which is known as the home (or local) environment externality is a critical factor in the positive inequality-growth relationship. The importance of the parental education input in the formation of the child's education has been stressed in the studies by Mosteller and Moynihan (1972), Becker and Tomes (1986) and Coleman (1990). The local human capital externalities may also perpetuate income inequality across generations (Benabou, 1994). In the mature stages of economic development, technological progress is positively related to the level of human capital in society (Schultz, 1975). The growth process may increase the rate of adoption of new technologies, which induces income convergence via diffusion. More specifically, as the investment in human capital of highly-educated individuals increases, the accumulated knowledge trickles down to the less-educated persons via a technological progress in production which is known as the global production externality (Galor and Tsiddon, 1997a: 94).

The relationship between educational inequality and economic growth is affected by *life expectancy*. Investment in human capital depends on the individual's life expectancy, which, in turn, depends to a large extent on the environment in which individuals grow up. An individual's level of human capital is not only an increasing function of the parental level of human capital, but also a function of the number of children born to their parents and life expectancy (de la Croix and Licandro, 1999; Blackburn and Cipriani, 2002; Kalemli-Ozcan, 2002). Children raised in poor families usually have a low life expectancy and work in low-skilled positions all their lives (Castello and Domenech, 2006).

Due to the lack of available data on educational inequality, little attention has been paid to the empirical impact of inequality on growth (i.e. Birdsall and Londono, 1997; López et al., 1998; Castello and Domenech, 2002). Most of empirical studies are based on the international data on educational attainment of Barro and Lee (1993; 1996; 2001). Birdsall and Londono (1997) explored the impact of the distribution of assets (both physical and human capital) on growth. They placed an emphasis on human capital accumulation via basic education and health. Their results illustrate a significant negative correlation between education dispersion and economic growth. López et al. (1998) demonstrated that the unequal distribution of education tends to have a negative effect on growth, while an increase in mean education has a positive impact. The impact of education on growth is also affected by the macroeconomic policy environment of a country, which determines what people can do with their education. For example, policy reforms can increase the returns from formal education and enhance the impact of education on growth through trade and investment. López et al. (1998) also showed that the distribution of education is related to technological progress and industrial upgrading. They emphasise the interaction of human capital distribution and policy reforms on economic growth. Finally, Castello and Domenech (2002) found a negative relationship between human capital inequality and growth for a broad panel of countries. This negative relationship exists not only through the efficiency of resource allocation, but also through a reduction in investment rates. They argue that countries which showed higher educational inequality had experienced lower investment rates and less efficiency in resource allocation than countries which registered lower levels of human capital inequality. The lower the investment rates and the less efficiency in the allocation of resources, the lower the growth rates. Their educational inequality measures provide more robust results than the income inequality measures.

To sum up, educational inequality is a significant factor in the economic process and economic growth rates. Although the theoretical and empirical literature on the impact of educational inequality on growth is more than limited, the existing literature provides much insight into the inequality-growth relationship.

2.7 Conclusion

While human capital is a multidimensional concept encompassing not only formal education, but also on-the-job training, study programmes for adults that are not organised by firms, migration, the acquisition of information about the economic system and investments in reputations and personal relationships; income is a straightforward concept. From a theoretical and empirical point of view, however, income and educational inequalities seem to be associated with one another. Wolf (2002: 18), for instance, pointed out that the more education and qualifications you acquire, the higher your income is likely to be, the more likely you are to be in work, to stay in work and to enjoy long-term employment on a permanent contract. Her arguments show that educational distribution is a basic determinant of income distribution, and vice versa. In addition, education is associated with labour market gains for individuals, including higher average post-tax earnings and an improved employment probability (Blöndal et al., 2002: 5).

Both income and educational distribution are basic determinants of regional economic growth analysis. First, educational distribution is regarded as the engine of economic growth and so is central to any modern economy. Wolf (2002: 244) argued that education now matters for growth more than ever before in history, but only when individuals have the right qualifications, they are studying the right subjects and they are in the right institutions. She also stressed that education still remains a key instrument for securing equal opportunities for people and for helping to improve their life chances. Second, income distribution is also a fundamental determinant in economic growth analysis. However, the impact of both income and educational inequality on growth is not clear-cut, at least at a regional level of analysis. This remains a challenge.

Overall, the relationship between inequalities and the process of economic development is still far from being understood and is, indeed, complex. The links between income inequality and growth and the links between educational inequality and growth are far less direct. The existing theoretical and empirical literature shows that there is a high correlation between income and educational inequalities, which, in turn, affect regional growth. It is still a great great challenge to find the determinants of regional growth, based on a microeconomic analysis of income and educational distribution. Nonetheless, as Krugman (1994: 29) states,

> 'economic theory suggests no particular connection between equity or justice and growth, and no evidence exists that income inequality has any large effects on the rate of economic growth, positive or negative'.

3 Chapter Three. An Analysis of European Income Distribution: Income Per Capita and Inequality

3.1 Introduction

This chapter focuses on income distribution in Europe. More specifically, it sets out to explore and analyse the average level of income distribution within regions and inequalities in that distribution, taking into consideration the spatial pattern and association between regions. The core methodology of this chapter is ESDA, focused on a variety of parametric methods. Spatial economic analysis reveals relationships in economic data that may be invisible, like the EU north-south income divide and the urban-rural divide. The empirical study encompasses a set of techniques aimed at describing and visualising spatial distributions of income per capita (both for the whole of the population and for normally working people), GDP per capita and income inequalities. The focus of attention is on identifying income differences across space rather than similarities.

The theoretical frameworks on neighbourhood effects, such as the endogenous growth theories (i.e. Romer, 1986; Lucas, 1988; Stokey, 1991; Lucas, 1993; Romer, 1994), the school of NEG and the cumulative causation theories (i.e. Rosenstein-Rodan, 1943; Perroux, 1950; Myrdal, 1957; Hirschman, 1958; Kaldor, 1970, 1981, 1985; Arthur, 1994) raise interesting questions about how interactions, which are summarised in spatial weights matrices (Abreu et al., 2004), can lead to emergent collective behaviour and aggregate patterns (Anselin, 2000). For instance, income is expected to be geographically concentrated in particular areas, due to certain processes such as market potential which induces factor inflows and raises local factor prices. Nevertheless, the theoretical framework of income agglomeration may be the natural advantages of the regions. Natural resources are not uniformly distributed across locations.[29] Regions exploit their comparative advantage and, thus, the regional concentration of economic activities arises as regions produce and export products that are relatively intensive in the use of their abundant resource (Kim, 1995). The first theoretical framework highlights the geography of distance between economic agents (the 'second' nature of

[29] It is on this unevenness that most of trade theory has been built (Fujita and Thisse, 2002: 6).

geography), while the second framework places an emphasis on the physical geography (the 'first' nature of geography) (Brakman et al., 2001). It is not the aim of this chapter to review this vast array of sources, but simply to focus on the patterns of income distribution. The null hypothesis of randomness is that the unequal distribution of economic activity is a natural outcome of a random process (Ellison and Glaeser, 1997), without any recourse to arguments about the 'first' and the 'second' nature of geography.

This chapter is structured in four sections. Section 3.2 examines the average income distribution within a region and that region's economic development. Hence, ESDA on income and GDP per capita is presented. Section 3.3 analyses the concept of income inequality in detail. More specifically, income inequality is conceptualised as average disproportionality (Allison, 1978; Firebaugh, 1999, 2003), while four income inequality indices are derived: the mean logarithmic deviation index, the Gini index, the generalised entropy index and the Atkinson index. These indices are evaluated against a set of four criteria: the scale independence, the population size independence, the additive decomposability and the principle of transfers. Section 3.4 applies ESDA on those indices to the European regions. It contains the measurement of income inequality within and between regions in the EU. In addition, it looks at whether the within-region income inequality constitutes the major portion of the income inequality in Europe. Finally, Section 3.5 compares the income per capita with income inequality within a region.

3.2 Defining and Measuring Regional Development

This section analyses regional development and consists of three subsections. The first subsection focuses on income per capita, while the second discusses GDP per capita. Both subsections place an emphasis on the treatment of spatial effects. The third subsection shows the correlation between these approaches.

3.2.1 Income Per Capita

Information on the average income (income per capita) of the European regions is collected by the regionalised microeconomic variable '*Total net personal income (detailed, NC, total year prior to the survey)*', which is extracted from the ECHP dataset. Two basic characteristics of this variable are that it is lagged variable and is measured in national currency. Personal income data are not comparable over time, because they are not in constant prices. They are adjusted to the same price level using the Harmonised Indices of Consumer Prices (HICPs).[30] Furthermore, income data must be comparable across countries and regions. Thus, they also converted into euros.[31] Data on income is collected not only for each individual in the household so as to measure income per capita for the population as a whole, but also for each normally working (15+ hours/week) individual[32] in the household in order to measure income per capita for normally working people.

3.2.1.1 Income Per Capita for the Population as a Whole

A first 'feel' for personal income data can be obtained by histograms. Figure 3.1 illustrates the income distribution in Europe in 1996, 1998 and 2000, for individuals whose personal income is not zero and is also smaller than 99 per cent of the total income distribution. Hence the income distributions below exclude persons who have no income from any source and the very rich. Each histogram also overlays a normal distribution for a comparable performance. The histograms show that income distribution in Europe changed slightly between 1996 and 2000. Among only the very low income levels between 1996 and 1998, income distribution moved to the right, showing some improvement at the lower levels of income. However, the density of income distribution at very low income levels is still very high, because individuals who are unemployed or inactive are included in the analysis. In 1998 and 2000, the European income distribution hit its highest point when the total personal income was 5,000 euros; while, in 1996 the European distribution reached a peak at around 1,000 euros. In 2000, between 1,000 and 10,000 euros the sample income density increases considerably and reaches a peak when income per capita is 5,000 euros, and then falls dramatically until it reaches a plateau between 7,000 and 10,000 euros. For all histograms, when the total net personal income is 10,000 euros, the European income distribution meets the normal distribution at the highest point. Therefore, when income

---

[30] According to the Eurostat' documentation '*HICPs are designed for international comparisons of consumer price inflation. They are used in the assessment of inflation convergence as required under Article 121 of the Treaty of Amsterdam (Article 109j of the Treaty of European Union)'*. [http://epp.eurostat.cec.eu.int (Eurostat, Statistical Office of the European Communities, Unit C5: Prices, L-2920 Luxembourg)].

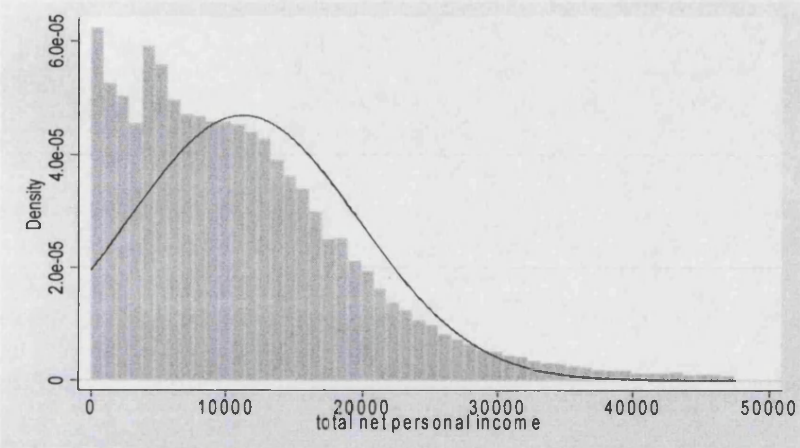
[31] Taking into account that the income variable is lagged one, for example, the personal income of Wave 3 (which corresponds to 1996) is divided by the 1995 relevant euro/ECU exchange rate.

[32] It is extracted from the variable '*Main activity status-Self defined (regrouped)*'.

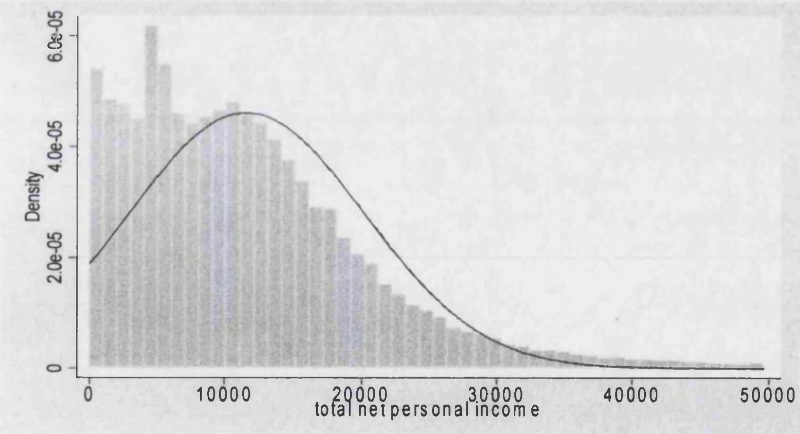
per capita is larger than 10,000 Euro, the European income distribution follows the normal distribution.

Figure 3.1: Histogram of the European Income Distribution in 1996, 1998 and 2000

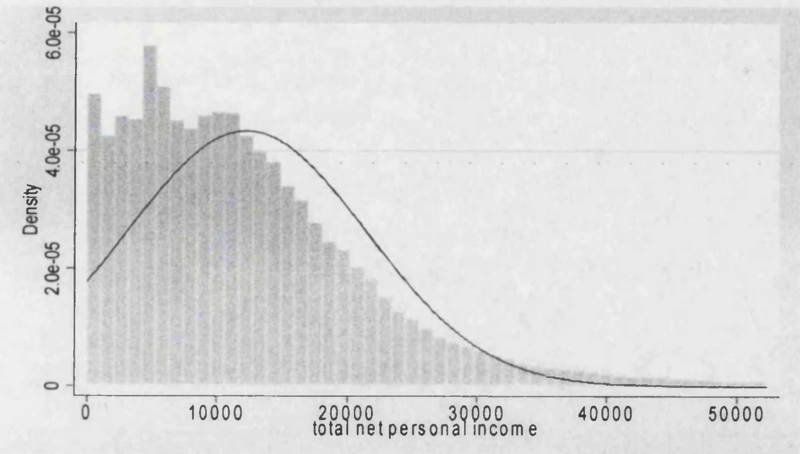
1996



1998



2000



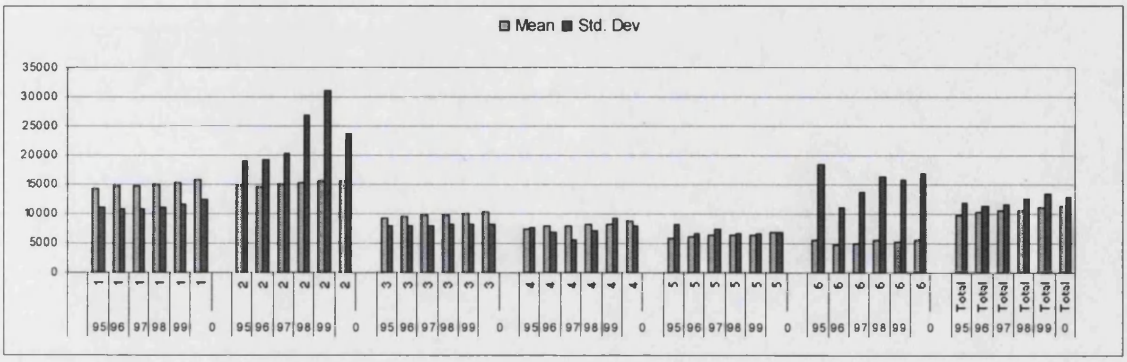
In order to gain a more accurate picture of the European income distribution, income is decomposed according to its sources. The main sources of personal income are collected from the variable '*Main sources of personal income*', which is extracted from the ECHP dataset. According to this variable, the main sources of personal income are:

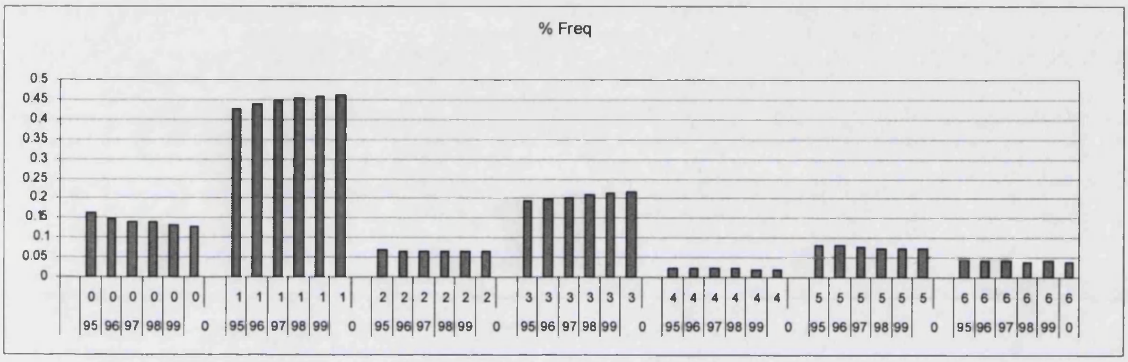
- person has no income from any source (code = 0);
- wages and salaries (code = 1);
- income from self employment or farming (code = 2);
- pensions (code = 3);
- unemployment and redundancy benefits (code = 4);
- any other social benefits or grants (code = 5); and
- private income (code = 6).

Figure 3.2 shows the fluctuation in the mean and the standard deviation of the European income distribution according to sources of personal income for the years 1995 to 2000. According to the figure, the mean of wages and pensions increased slightly, while their standard deviation remained constant. The evolution of personal income per capita coming from self employment or farming remains the same. In contrast, there is a considerable variation in standard deviation, which reaches the highest point in 1999. Between 1995 and 2000, the evolution of both the mean and the standard deviation of the unemployment and social benefits remained constant. The evolution of private income remained the same, while its standard deviation, which started from a high value in 1995, reached its lowest point in 1996, and has risen steadily since 1998 to remain the same since 2000. The standard deviations of income coming from self employment and of private income are much higher than their average values. The figure also shows the percentage of the European income distribution per source of personal income. Income from salaries represents the largest percentage.

The data on income per capita are spatial data and specifically irregular lattice data, because the size of each region differs. The average income of a region has the properties of spatially aggregated data.

Figure 3.2: Evolution of the European Income Distribution According to Main Source of Personal Income

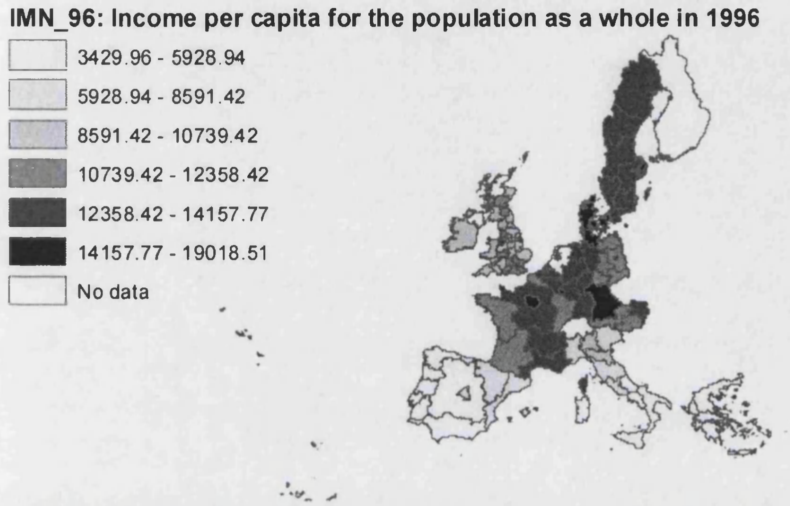


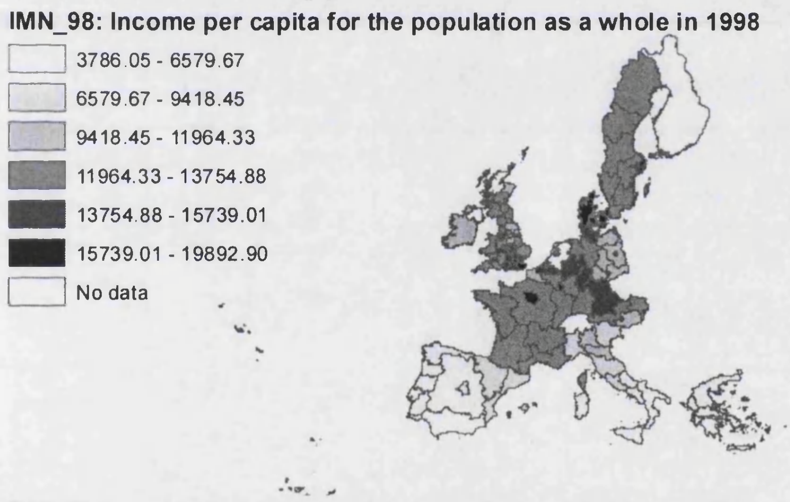


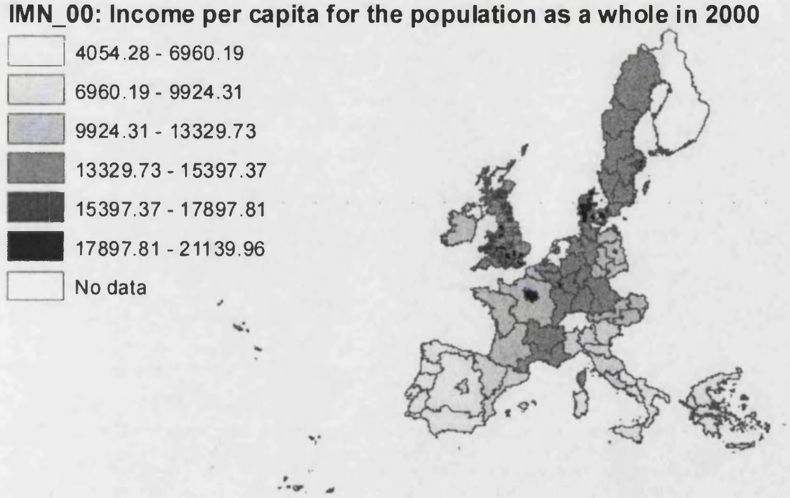
An initial step of ESDA is to map income per capita in order to gain a spatial view of the data and, among other aims, to see whether incomes per capita are randomly distributed over space or there are similarities between regions. Figure 3.3 shows the spatial distribution of income per capita in the EU in 1996, 1998 and 2000. From 1996 to 2000, the wealthier regions were Île de France, Luxembourg, Belgium and Denmark. There are striking disparities in income per capita among different parts of Europe, particularly between the northern and the southern regions. Income per capita is typically half of the EU average in the southern periphery, stretching from Greece to Southern Italy (Sicilia, Sud, Campania and Abruzzo-Molise), western Spain (Canarias, Sur, Centro and Noroeste) and Portugal, over the period 1996–2000. The economic conditions of surrounding regions seem to influence the economic development perspectives of this region. Baumont et al. (2003) argued that a poor region surrounded by poor regions will remain in that state of economic development, whereas a poor region surrounded by richer regions has a greater probability that it will reach a higher state of economic development. Another important feature displayed this figure is the high average income in city-regions. The higher the urbanisation level of a region, the higher its income per capita. This figure represents the distribution of income per capita without any information about the existence and extent of spatial autocorrelation.

However, it illustrates the 'unevenness' in income per capita, which appears to be concentrated in particular areas. This may indicate a positive spatial autocorrelation phenomenon.

Figure 3.3: Spatial Distribution of Income Per Capita for the Population as a Whole (IMN) in 1996, 1998 and 2000

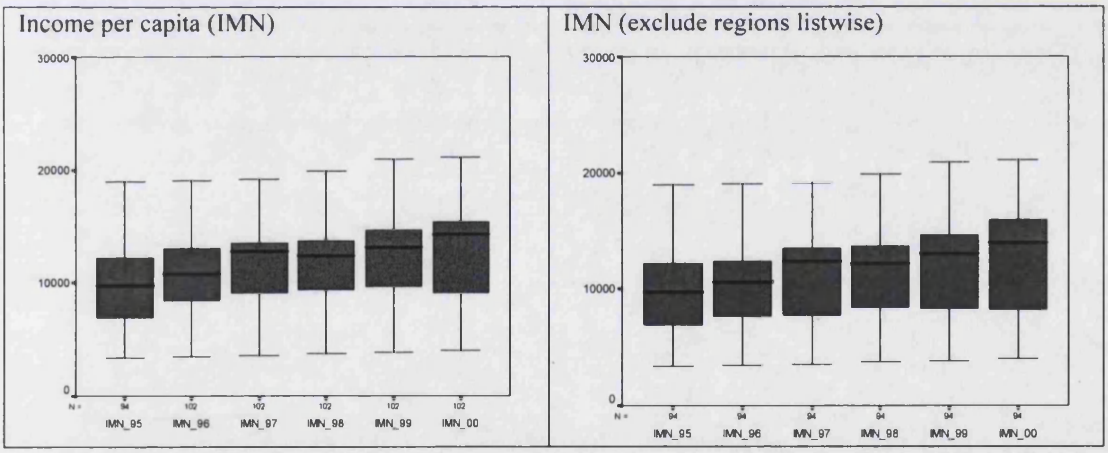






A better picture of income per capita within regions can be obtained by using the univatiate boxplot technique. The boxplots for income per capita in European regions between 1995 and 2000 are shown in Figure 3.4. The median income increased gradually from 1995 to 2000. The distributions of income per capita are fairly compact, because the whiskers are, in fact, the extreme values. The interquartile range is longer in 2000 than from 1995 to 1999. Furthermore, the variation in the whiskers is greater in 1999 and 2000 than in 1996, 1997 and 1998. The European distribution of income per capita accepts the normality in 1995 and 1996, but rejects it over the period 1997–2000.[33] The ratio of skewness to standard error indicates a right tail in 1995 and a left tail in 1996. Looking behind the boxplots, Luxemburg has the highest average income among the European regions. In contrast, Portuguese, Greek and Spanish regions register the lowest income per capita. For example, the income per capita of the Greek regions is approximately one third that of Luxemburg. The variation in average income among the United Kingdom regions is greater than that found in the remaining European regions.

Figure 3.4: Boxplot for Income Per Capita for the Population as a Whole (IMN)



A spatial autocorrelation for income per capita identifies the relationship behind the similarity of income per capita and spatial proximity. Considering three different spatial weights schemes, different trends in the distribution of income per capita exist over space. First, constructing the rook first order contiguity spatial weights for income per capita, Moran's I statistic (Moran, 1950) is positive and statistically significant, which suggests that the null hypothesis of no spatial autocorrelation should be rejected (Table

[33] The ratio of skewness to standard error is 0.40 in 1995, -1.00 in 1996, -2.66 in 1997, -2.29 in 1998, -2.32 in 1999 and -2.05 in 2000.

3.1). The distribution of income per capita is, indeed, clustered throughout the period of study. The rich were concentrated in particular European regions over the period 1995–2000. Spatial dependence analysis also shows that the bivariate Moran's I statistic between a region's income per capita in 1998 and the neighbouring regions' income per capita in 1996 (which is the space-time correlation of income per capita in 1998) is 0.6149. Second, the short evolution of the standardised values of Moran's I statistics when I consider the 3-nearest neighbours weights schemes is similar to that of the rook first order contiguity. Third, the spatial autocorrelation of the threshold distance schemes is lower than for the previous schemes. Briefly, Moran's I statistics for any spatial weights schemes disprove the hypothesis that income per capita is randomly distributed over space. Moran's I statistics lead to the same results for the sign (positive) and significance of global spatial dependence, highlighting the robustness of the results, with regard to the choice of the spatial weights matrix. However, the standardised values of the spatial autocorrelation and the space-time correlation appear to be very high, indicating a spatial scale problem (Ertur and Le Gallo, 2003: 64).

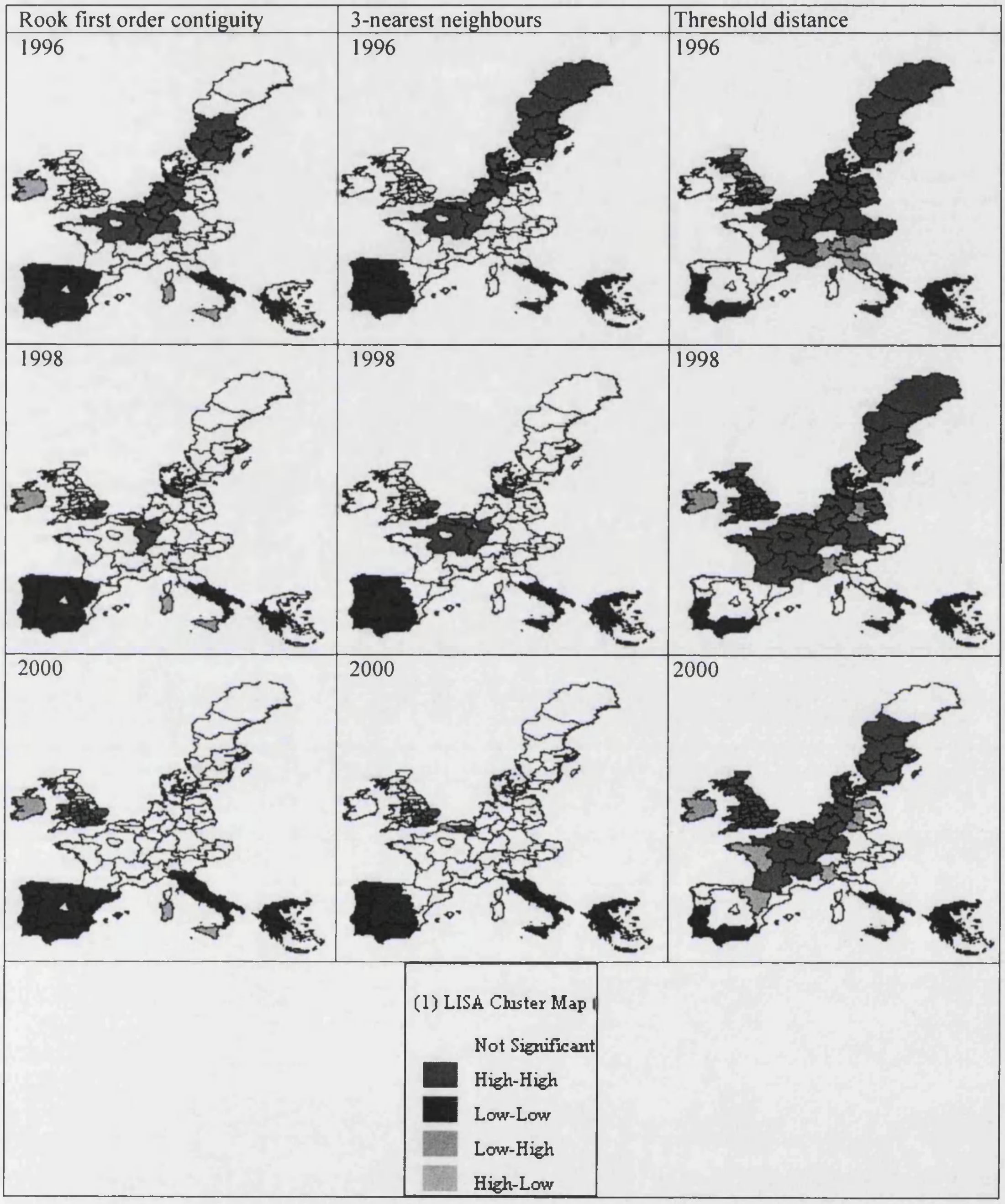
Table 3.1: Moran's I for Income Per Capita of the Population as a Whole (IMN)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996	0.6605	-0.0106	0.0739	9.0812	0.7830	-0.0050	0.0768	10.2604	0.4288	-0.0107	0.0224	19.6205
	1997	0.6565	-0.0103	0.0747	8.9264	0.8024	-0.0069	0.0719	11.2559	0.4699	-0.0110	0.0225	21.3733
	1998	0.6499	-0.0079	0.0765	8.5987	0.7968	-0.0092	0.0742	10.8625	0.4602	-0.0111	0.0213	22.1268
	1999	0.6644	-0.0151	0.0750	9.0600	0.8100	-0.0093	0.0705	11.6213	0.4669	-0.0104	0.0220	21.6955
	2000	0.7027	-0.0040	0.0757	9.3355	0.8345	-0.0115	0.0739	11.4479	0.4736	-0.0093	0.0221	21.8507
Space-time correlation	1998	0.6149	-0.0081	0.0733	8.4993	0.7358	-0.0081	0.0698	10.6576	0.4267	-0.0095	0.0217	20.1014
	2000	0.6535	-0.0086	0.0736	8.9959	0.7846	-0.0083	0.0726	10.9215	0.4580	-0.0098	0.0214	21.8598
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.6713	-0.0048	0.0755	8.9550	0.7646	-0.0131	0.0784	9.9196	0.3506	-0.0120	0.0223	16.2601
	1996	0.6513	-0.0113	0.0750	8.8347	0.7641	-0.0135	0.0753	10.3267	0.3934	-0.0114	0.0226	17.9115
	1997	0.6629	-0.0104	0.0719	9.3644	0.7981	-0.0118	0.0768	10.5456	0.4695	-0.0106	0.0229	20.9651
	1998	0.6578	-0.0079	0.0778	8.5566	0.7983	-0.0074	0.0785	10.2637	0.4597	-0.0101	0.0227	20.6960
	1999	0.6751	-0.0053	0.0762	8.9291	0.8134	-0.0096	0.0761	10.8147	0.4712	-0.0089	0.0238	20.1723
	2000	0.7145	-0.0091	0.0758	9.5462	0.8387	-0.0058	0.0784	10.7717	0.4834	-0.0109	0.0226	21.8717
Space-time correlation	1998	0.6193	-0.0108	0.0758	8.3127	0.7338	-0.0088	0.0699	10.6237	0.4146	-0.0106	0.0224	18.9821
	2000	0.6620	-0.0091	0.0756	8.8770	0.7866	-0.0152	0.0736	10.8940	0.4595	-0.0110	0.0221	21.2896

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

The use of LISA allows one to assess the regional structure of spatial autocorrelation (Anselin, 1995a). Figure 3.5 demonstrates the income per capita cluster maps for 1996, 1998 and 2000 for three spatial weights schemes. Both the rook first order contiguity and the 3-nearest neighbours weights schemes show that clusters of poorer regions were found in the southern periphery and did not change between 1996 and 2000. By contrast, the number and the size of richer clusters declined over time. Income is concentrated in specific areas, which are characterised by their financial and business services and are the centres of public administration, such as London, Paris and Luxembourg. In 1996, for example, the income per capita was well above average in the more central areas stretching from eastern France (Bassin Parisien, Centre-Est and Mediterranee) through Belgium and Germany. Activity in those regions is concerned with services and manufacturing. In 1996, the income per capita of manufacturing regions declined and, in 2000, it declined even more. The cluster of the southern United Kingdom is characterised by a high level of urbanisation. To sum up, the choice of the weights matrix is crucial in ESDA so as to identify the spatial clusters.

Figure 3.5: Cluster Map for Income Per Capita for the Population as a Whole (IMN) in 1996, 1998 and 2000



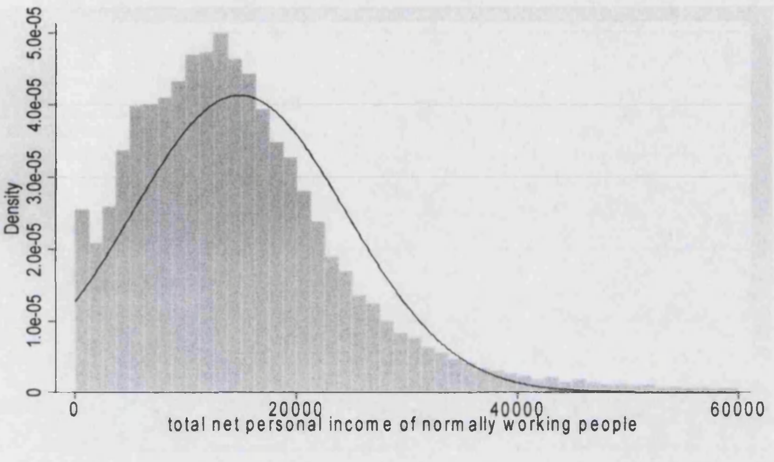
All the nine cluster maps show a strong north-south divide and reveal the presence of spatial heterogeneity in the form at least two spatial clusters of rich and poor regions. The geographical distributions of the European regions firstly exhibit an income polarisation pattern between rich regions in the north and poor regions in the south. This evidence can, in fact, be linked to several results for the NEG theories, and to the possibility of multiple spatial equilibria (Krugman, 1991a) and the club convergence theories of Azariadis and Drazen (1990) and Durlauf and Johnson (1995) (Baumont et al., 2003). Secondly, the results clearly show the persistence of income disparities among the European regions over time, following a pattern of an urban-rural divide. To sum up, spatial dependence and spatial heterogeneity are inevitable features of regional income per capita variation analysis.

3.2.1.2 Income Per Capita for Normally Working People

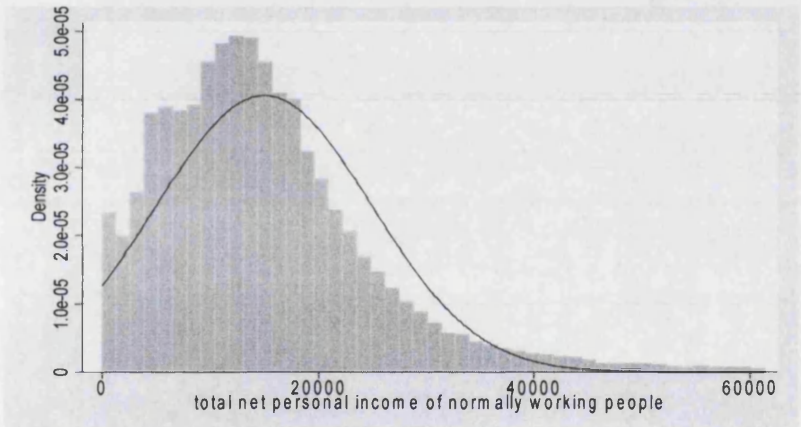
Figure 3.6 illustrates the income distribution in Europe in 1996, 1998 and 2000, for normally working people whose personal income is not zero and is also smaller than 99 per cent of total income distribution. Each histogram, once again, overlays a normal distribution to show comparable performance. The histograms show that the income distribution in Europe among those people normally in work has changed slightly between 1996 and 2000. The density of income distribution at the very low income levels for normally working people is lower than for the whole of the population. At the very low income levels, income distribution moved somewhat to the right between 1996 and 1998, marking an improvement in the economic position of the low income strata and a decrease in income inequality. Income distribution in Europe for this population reaches a peak when income is approximately 12,000 euros and then it follows the normal distribution.

Figure 3.6: Histogram of the Income Distribution in Europe among Normally Working People in 1996, 1998 and 2000

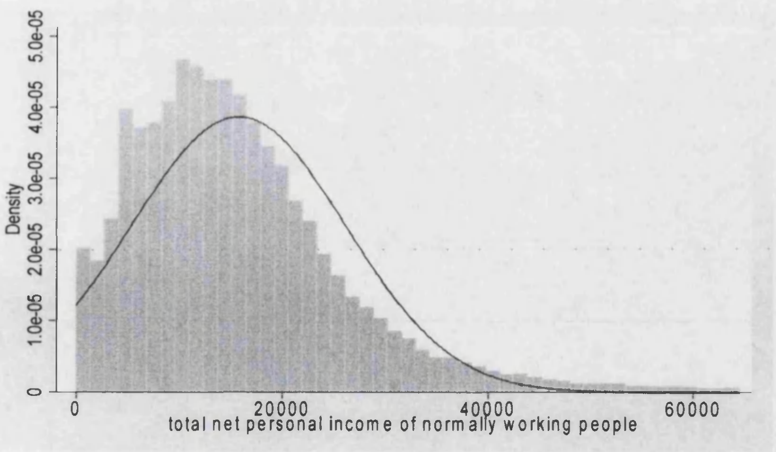
1996



1998

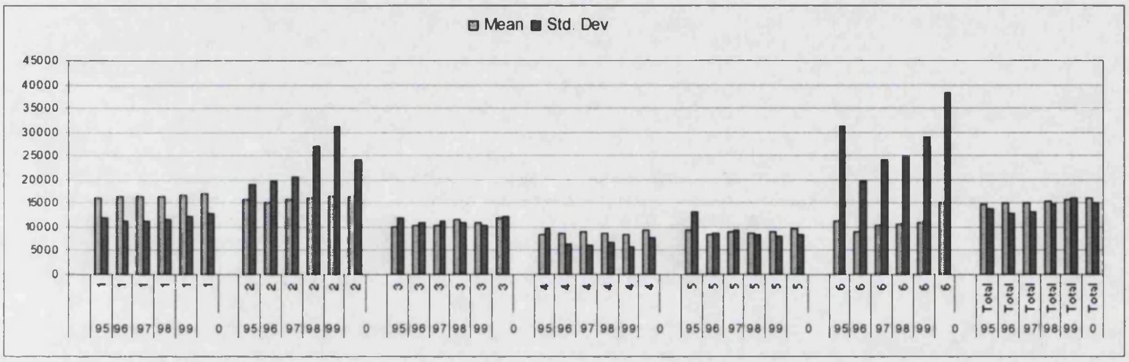


2000



Once more, in order to gain a more accurate picture of the income distribution in Europe, income is decomposed according to its sources. Figure 3.7 shows the short evolution of income distribution for normally working people according to the main sources of personal income. The evolution of income per capita in Europe and its sources remains the same. However, the amount of private income per capita increased considerably between 1999 and 2000. There is a considerable variation in standard deviation of wages and private income. Finally, income from salaries accounts for the highest percentage (78 per cent) of personal income. That percentage is far higher than the respective percentage for the whole of the population (45 per cent).

Figure 3.7: The Evolution of the Income Distribution in Europe Among Normally Working People per Main Sources of Personal Income



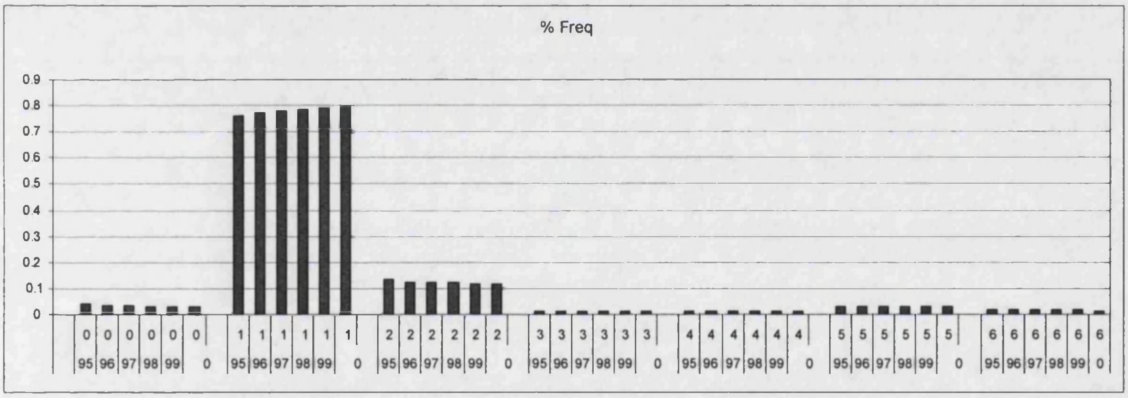
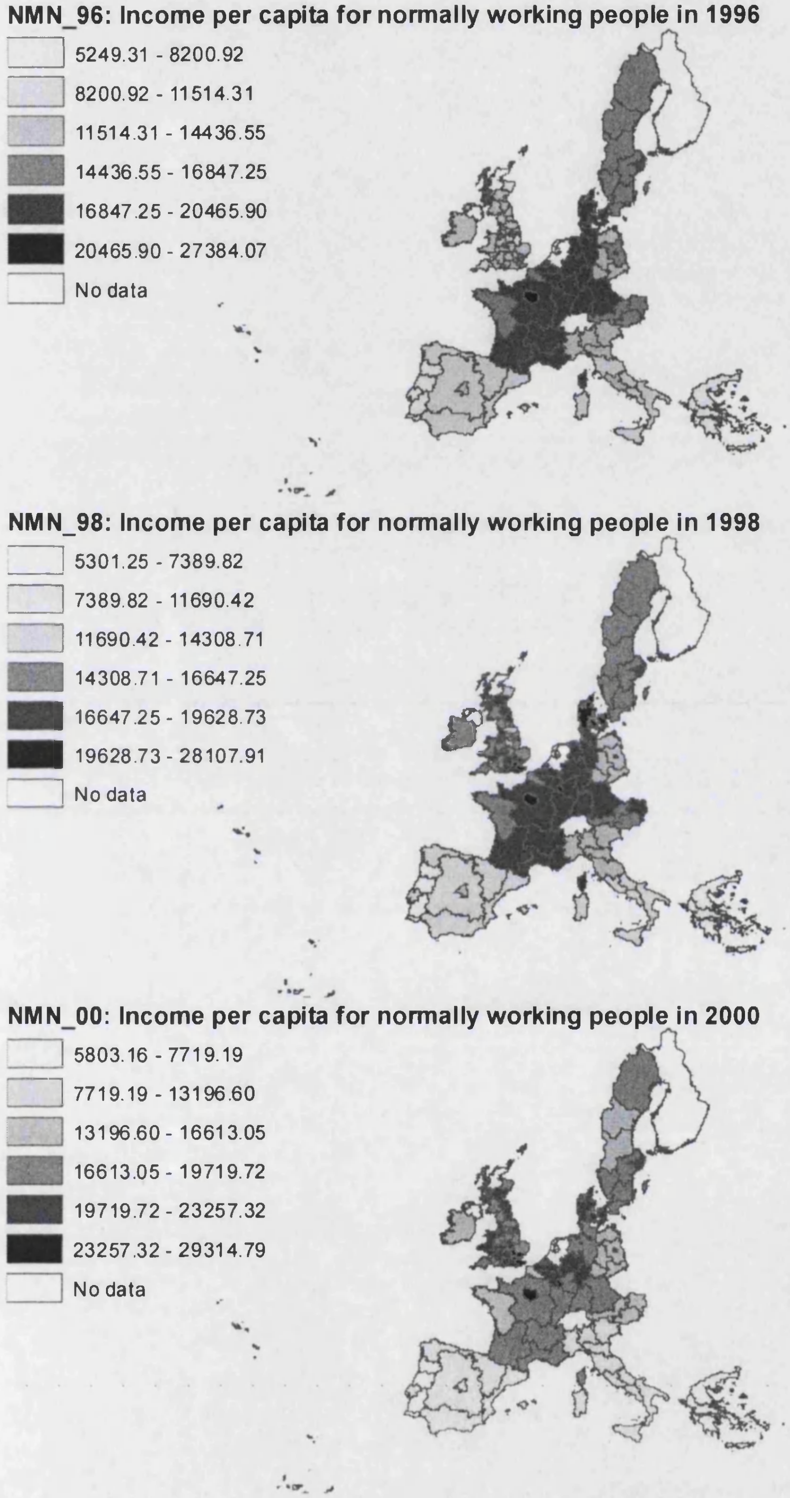


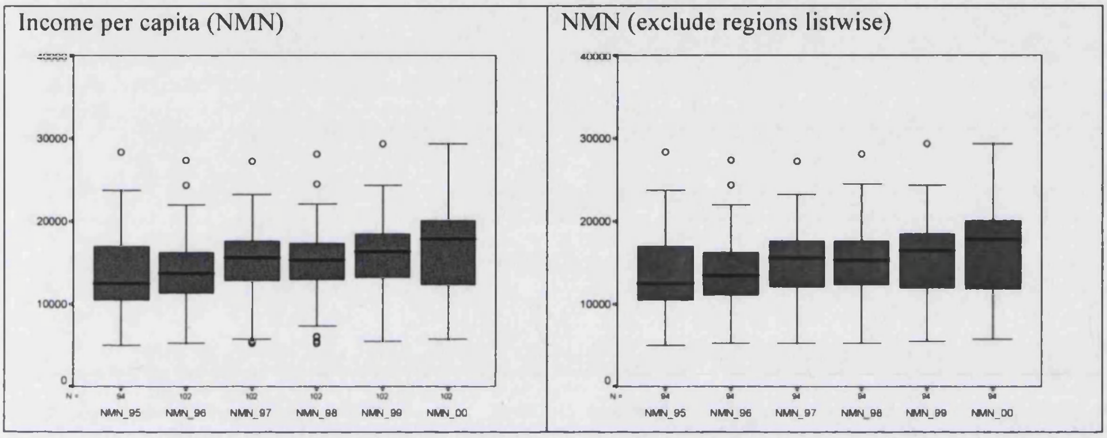
Figure 3.8 shows the geographical distribution of income per capita among people normally in work in 1996, 1998 and 2000. The distribution is clustered throughout the period under study. There are striking disparities in income per capita between different parts of Europe, not so much between the northern and southern regions, but in particular between the core and the periphery. Another important feature is that income per capita among normally working people is higher in city-regions.

Figure 3.8: Spatial Distribution of Income Per Capita for Normally Working People (NMN) in 1996, 1998 and 2000



The boxplots for the income per capita of normally working people in the European regions between 1995 and 2000 are shown in Figure 3.9. The median increased gradually from 1995 to 2000, as it did for the income per capita of the whole population. However, the distribution of income per capita among normally working people is less compact than for the whole population. Luxemburg and Île de France are outliers at the upper end of the distributions, while the Portuguese regions (Centro, Algarve, Madeira and Alentejo) are outliers at the lower end of the distributions in 1998. The interquartile range is greater in 2000 than from 1995 to 1999, as it is for income per capita for the whole of the population as well. The distributions accept normality over the period 1996–2000, but reject it in 1995. In 1995 and 1996, the ratio of skewness to standard error is positive which indicates a right tail, whereas from 1997 to 2000 that ratio is negative which indicates a left tail.[34]

Figure 3.9: Boxplot for Income Per Capita of Normally Working People (NMN)



Note: extreme cases and outliers are sorted by descending order:
NMN: LU (upper end) in 1995; LU, FR1 (upper end) in 1996; PT3, PT12, PT14 and PT15 (lower end) and LU (upper end) in 1997; PT12, PT15, PT3 and PT14 (lower end) and FR1 and LU (upper end) in 1998; LU (upper end) in 1999.
NMN (exclude regions listwise): LU (upper end) in 1995; LU, FR1 (upper end) in 1996; LU (upper end) in 1997; LU (upper end) in 1998; LU (upper end) in 1999 (see Appendix A1.1).

The spatial dependence for income per capita of normally working people shows that income in a particular region is likely to contribute to output gains in adjoining regions (Table 3.2). The distribution of income per capita is by nature clustered over the whole period. The univariate and bivariate Moran's I statistics computed using the rook first order contiguity, the 3-nearest neighbours and the threshold distance weights matrices are high and statistically significant. As for income per capita for the whole of the population, the standardised values of the statistics remain approximately the same between 1995 and 2000, indicating a global tendency towards geographical clustering of similar regions in terms of income per capita. If the average income of one region increases, all regions benefit from the spillovers which are summarised in a spatial weights matrix. For instance, if one region attracts highly-educated workers whose wages are high, all remaining regions may benefit from that attraction. Another example

[34] The ratio of skewness to standard error is 2.20 in 1995, 0.74 in 1996, -1.92 in 1997, -1.05 in 1998, -1.45 in 1999 and -1.63 in 2000.

is that public infrastructure investments may increase the home market effects of a region and, thus, the wages, which, in turn, may change the competitive and comparative advantages of all regions. The speed of diffusion is influenced by the region-specific characteristics and the availability of normally working people in neighbouring regions.

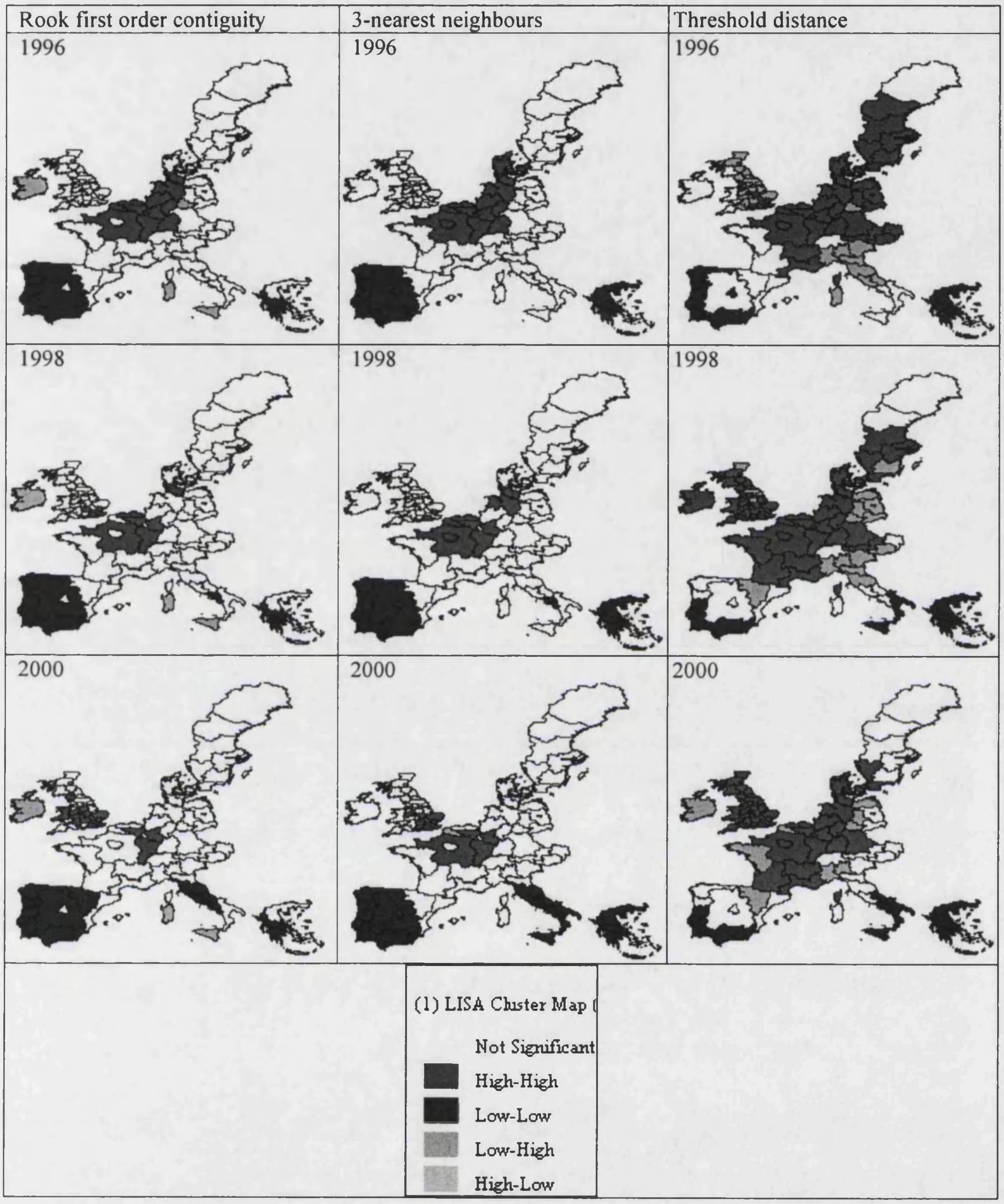
Table 3.2: Moran's I for Income Per Capita of Normally Working People (NMN)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996	0.6314	-0.0090	0.0730	8.7726	0.7545	-0.0105	0.0732	10.4508	0.3392	-0.0116	0.0213	16.4695
	1997	0.6080	-0.0092	0.0741	8.3293	0.7679	-0.0084	0.0760	10.2145	0.4361	-0.0091	0.0231	19.2727
	1998	0.5868	-0.0053	0.0745	7.9477	0.7433	-0.0094	0.0740	10.1716	0.4095	-0.0099	0.0221	18.9774
	1999	0.6119	-0.0082	0.0747	8.3012	0.7618	-0.0079	0.0728	10.5728	0.4310	-0.0102	0.0231	19.0996
	2000	0.6668	-0.0159	0.0733	9.3138	0.8003	-0.0129	0.0729	11.1550	0.4590	-0.0093	0.0221	21.1900
Space-time correlation	1998	0.5586	-0.0113	0.0701	8.1298	0.6892	-0.0113	0.0693	10.1082	0.3551	-0.0094	0.0221	16.4932
	2000	0.5828	-0.0066	0.0730	8.0740	0.7216	-0.0106	0.0715	10.2406	0.4185	-0.0086	0.0212	20.1462
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.6365	-0.0065	0.0746	8.6193	0.7237	-0.0122	0.0743	9.9044	0.2747	-0.0111	0.0234	12.2137
	1996	0.6304	-0.0106	0.0743	8.6272	0.7545	-0.0167	0.0754	10.2281	0.3221	-0.0106	0.0244	13.6352
	1997	0.6149	-0.0083	0.0768	8.1146	0.7745	-0.0107	0.0756	10.3862	0.4420	-0.0106	0.0227	19.9383
	1998	0.5929	-0.0093	0.0777	7.7503	0.7522	-0.0085	0.0771	9.8664	0.4150	-0.0098	0.0231	18.3896
	1999	0.6215	-0.0092	0.0762	8.2769	0.7719	-0.0108	0.0748	10.4639	0.4404	-0.0107	0.0224	20.1384
	2000	0.6770	-0.0109	0.0775	8.8761	0.8096	-0.0098	0.0770	10.6416	0.4707	-0.0107	0.0224	21.4911
Space-time correlation	1998	0.5648	-0.0093	0.0698	8.2249	0.6987	-0.0104	0.0738	9.6084	0.3530	-0.0096	0.0223	16.2601
	2000	0.5901	-0.0142	0.0735	8.2218	0.7305	-0.0067	0.0746	9.8820	0.4241	-0.0106	0.0217	20.0323

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

It can be seen that most European regions are characterised by positive spatial association. The study of the geographical distribution of income per capita in Europe over the period 1995–2000 using cluster maps highlights the importance of spatial interactions and geographical location in income distribution issues. Since economic activities are not randomly distributed in space, income per capita remains geographically concentrated. The estimation and the occurrence of interregional externalities depend on the choice of the weights matrix. Figure 3.10 illustrates the cluster map for the income per capita of normally working people in 1996, 1998 and 2000 using three weights matrices. The cluster maps of both the rook first order contiguity and the 3-nearest neighbours weights schemes highlight the core-periphery pattern. Core regions (north-east France, Belgium, Luxemburg and north-west Germany) with a relatively high income per capita are and remain located close to other core regions with a relatively high income per capita. Conversely, periphery regions (Portugal, western Spain, southern Italy and Greece) with a relatively low income per capita tend to be in the pull of other core regions with a relatively low income per capita. Taking into account the threshold distance weights schemes, the core clusters are further expanded including, for instance, southern British and Swedish regions. Finally, the economic surroundings of a European region seem to influence the economic development perspectives of that region. A poor normally working person who lives in a low income per capita region which is surrounded by other poor regions will probably remain at that stage of income levels; whereas a rich person who lives in a region which is surrounded by richer regions should remain at a high income level. Hence local economic externalities influence regional economic development.

Figure 3.10: Cluster Map of Income Per Capita of Normally Working People (NMN) in 1996, 1998 and 2000



The cluster maps highlight a certain level of spatial heterogeneity hidden within the global spatial dependence pattern. One source of spatial heterogeneity is the urbanisation level within a region, which seems to be negatively correlated with the income per capita of normally working people. The role of cities in regional development is emphasised. The second spatial regime is the core-periphery pattern. The development of new growth theory, cumulative causation theories and NEG have made major contributions to the understanding of the core-periphery pattern. Both spatial regimes show that the locations of income activities for working people are spatially clustered according to certain agglomerated and cumulative processes.

Table 3.3 shows that the linear relationship between the income per capita of the whole population and the income per capita of normally working people is positive, statistically significant and very high.

Table 3.3: Pearson Correlation between the Income Per Capita of the Whole Population (IMN) and the Income Per Capita of Normally Working People (NMN)

1995	1996	1997	1998	1999	2000
0.957 (0.000)** 94	0.955 (0.000)** 94	0.968 (0.000)** 94	0.967 (0.000)** 94	0.976 (0.000)** 94	0.984 (0.000)** 94
	0.950 (0.000)** 102	0.963 (0.000)** 102	0.963 (0.000)** 102	0.973 (0.000)** 102	0.981 (0.000)** 102

Note: ** correlation is significant at the 0.01 level (2-tailed).

3.2.2 GDP Per Capita

GDP per capita is measured using data extracted from the Eurostat's Regio database and is calculated in terms of Purchasing Power Parity (PPP)[35] to take account of differences in price levels. GDP per capita is the standard measure of the size and performance of a regional economy. It is designed to measure the total output in a particular region, including services (European Commission, 1999). More specifically, GDP is the total output of goods and services for final use produced by a regional economy, by both residents and non-residents, regardless of the allocation to domestic and foreign claims.[36] The range of the GDP per capita time-series analysis covers the period from 1995 to 2002.

There are some mismatches between the regional division in the ECHP and the Eurostat's Regio databank. For instance, the Eurostat's Regio database does not provide economic data for the region of 'Rheinland-Pfalz+Saarland' (dex), but for the German regions of Rheinland-Pfalz (deb) and Saarland (dec). Hence, the GDP per capita of 'Rheinland-Pfalz+Saarland' is approximately the average GDP per capita of Rheinland-

[35] According to the Eurostat' documentation '*PPP is a currency conversion rate that converts economic indicators expressed in a national currency to an artificial common currency that equalises the purchasing power of different national currencies. In other words, PPP is both a price deflator and a currency converter; it eliminates the differences in price levels between countries in the process of conversion to an artificial common currency, called Purchasing Power Standard*' (http://epp.eurostat.cec.eu.int/).

[36] www.undp.org/hdr2001/ - United Nations Development Programme.

Pfalz and Saarland weighted by their population size. This is expressed in the following form.

$$GDPPC(dex) = \frac{pop(deb)}{pop(deb + dec)} GDPPC(deb) + \frac{pop(dec)}{pop(deb + dec)} GDPPC(dec)$$

Other merged regions are Nord Ovest (it1), Nord Est (it3), Centro (it5), Abruzzo-Molise (it7), Sud (it9), Cornwall, Devon (uk62), Clwyd, Dyfed, Gwynedd, Powys (uk91) and Gwent, Mid-South-West Glamorgan (uk92), which are displayed in Appendix A1.1.

GDP per capita, like income per capita, are spatially aggregated data and the 'modifiable areal unit problem' and the problem of spatial autocorrelation and heterogeneity may be encountered. Additionally, GDP per capita is a seasonally adjusting variable. The 'smoothing' procedures (or the 'manipulation' of data)[37] used by government agencies often build autocorrelation into series that might otherwise be non-autocorrelated (Greene, 2003).

Considering first ESDA, I map the data in order to get a visual picture and to see whether macroeconomic data are randomly distributed over the EU or whether there are similarities among regions. Figure 3.11 shows the spatial distribution of regional GDP per capita in the EU in 1996, 1998 and 2000. It demonstrates that there are disparities in economic performance between different regions of Europe. GDP per capita is approximately two-thirds of the EU average in the Cohesion countries. It is well above average in the more central areas of Europe, including northern Italy (Nord Ovest, Lombardia, Nord Est and Emilia-Romagna), Austria (Ostösterreich and Westösterreich) and western Germany (Baden-Württemberg, Bayern and Hessen), in 1998 and 2000. By contrast, the clusters of poorer regions seem to be in the southern periphery of Europe, stretching from Greece through southern Italy and south-western Spain and Portugal. However, the scale of disparities across the Union depends on the type of region and the specific problems encountered in particular countries, which go beyond the simple core-periphery distinction (European Commission, 1999). Generally speaking, regional disparities have not changed dramatically from 1995 to 2002.

[37] Gujarati (2003) refers to interpolation and extrapolation as sources of 'manipulation' of data.

Figure 3.11: Spatial Distribution of GDP Per Capita (GDPPC) in 1996, 1998 and 2000

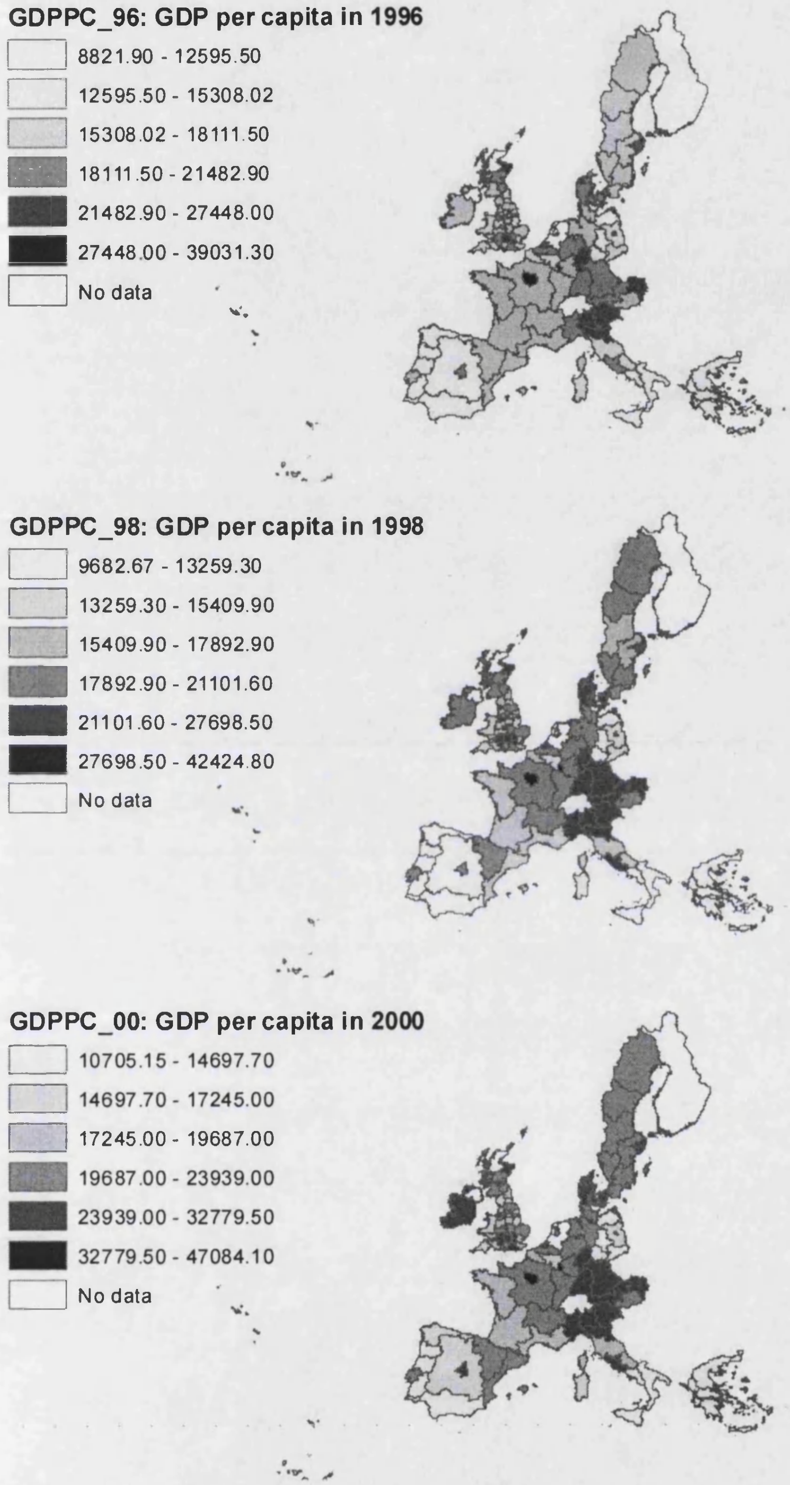
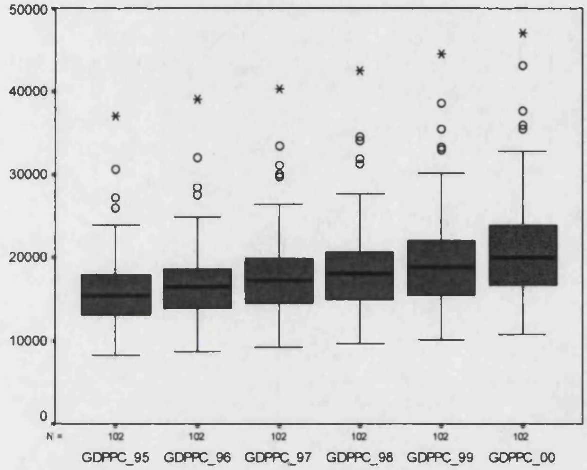


Figure 3.12 displays the univariate boxplot for GDP per capita within European regions from 1995 to 2000. It shows that the outliers and extreme cases are city-regions, which are subject to many externalities (Anas et al., 1998). Bruxelles-capitale, which is the centre for European public administration, was an extreme case between 1995 and 2000. Luxembourg, which is also a centre for European economic and monetary policy decisions, Hamburg and Greater London, in which inner London constitutes one of the

world's financial, economic and business centres, are all outliers. One problem encountered in measuring GDP per capita in city-regions is that they are underbounded regions, which are smaller than their Functional Urban Regions (FURs) (Cheshire and Hay, 1988). The administrative definition of cities in Europe bears no constant relation to any functional definition (Cheshire and Hay, 1988: 15). The administrative definition of cities (i.e. NUTS) does not capture the economic sphere of influence of a city. Conversely, '*FURs are functional in that their boundaries are determined on the basis of economic relationships rather than history or political divisions*' (Cheshire and Hay, 1988: 15). The bigger the city, the smaller the spatial units chosen, the greater the measurement bias is likely to be (Cheshire and Hay, 1988: 18). For instance, the Greater London area is considerably smaller than the FUR of London (Cheshire and Hay, 1988: 18). The size of the region matters for spatial analysis. The fact that central cities are likely to provide public services that benefit populations living in the rest of the metropolitan area but working, studying or shopping in the central city (Greene et al., 1974) is not observable in large city-regions. The interdependencies between central cities and their suburbs are not captured. This figure also shows that the difference between the first and third quartiles and the median rose gradually. The growth rates of Bruxelles-capitale, Hamburg and Greater London were found to have increased by following the growth rates of the median, while the growth rate of Luxemburg was higher. Moreover, the distributions are skewed, although much of that skewness is due to the extreme value and outliers in the higher end of the distributions. The European distribution of GDP per capita rejects the normality over 1995–2000.[38] The ratio of skewness to standard error is positive and greater than two, which indicates a long right tail.

[38] The ratio of skewness to standard error is 5.73 in 1995, 5.82 in 1996, 5.65 in 1997, 5.92 in 1998, 6.25 in 1999 and 5.73 in 2000.

Figure 3.12: Boxplot for GDP Per Capita (GDPPC)



Note: extreme cases and outliers are sorted in descending order: BE1, DE6, LU, FR1 and UK55 in 1995, 1996 and 1997; BE1, DE6, LU, UK55 and FR1 in 1998; BE1, LU, DE6, UK55 and FR1 in 1999 and 2000 (see Appendix A1.1).

Similar to the construction of the spatial weights matrices for income per capita, the rook first order contiguity, the 3-nearest neighbours and the threshold distance band spatial weights schemes are used in order to create the weights matrices for GDP per capita (Table 3.4). For instance, Moran's I statistic computed using the contiguity weights schemes is 0.2515 in 1995. It shows that there is a low positive spatial autocorrelation of GDP per capita. Due to the low value of the Moran's I statistic, it would appear that GDP per capita is more randomly distributed over space than income per capita (either for the whole of the population or for normally working people). Considering the bivariate measure of spatial correlation, I examined whether a region's GDP per capita in a given year is correlated with the lagged GDP per capita in neighbouring regions. The space-time correlation is 0.2310 in 1998 and 0.2069 in 2000. This may be due to the fact that common regional activities in neighbouring regions (i.e. public infrastructures) and common policies across neighbouring regions (i.e. structural funds) affect all regions lagged. Moran's I statistic computed using the 3-nearest neighbours and the threshold distance is 0.3175 and 0.1429, respectively, for 1995. The standardised values of Moran's I statistics remain approximately the same for the period between 1995 and 2000.

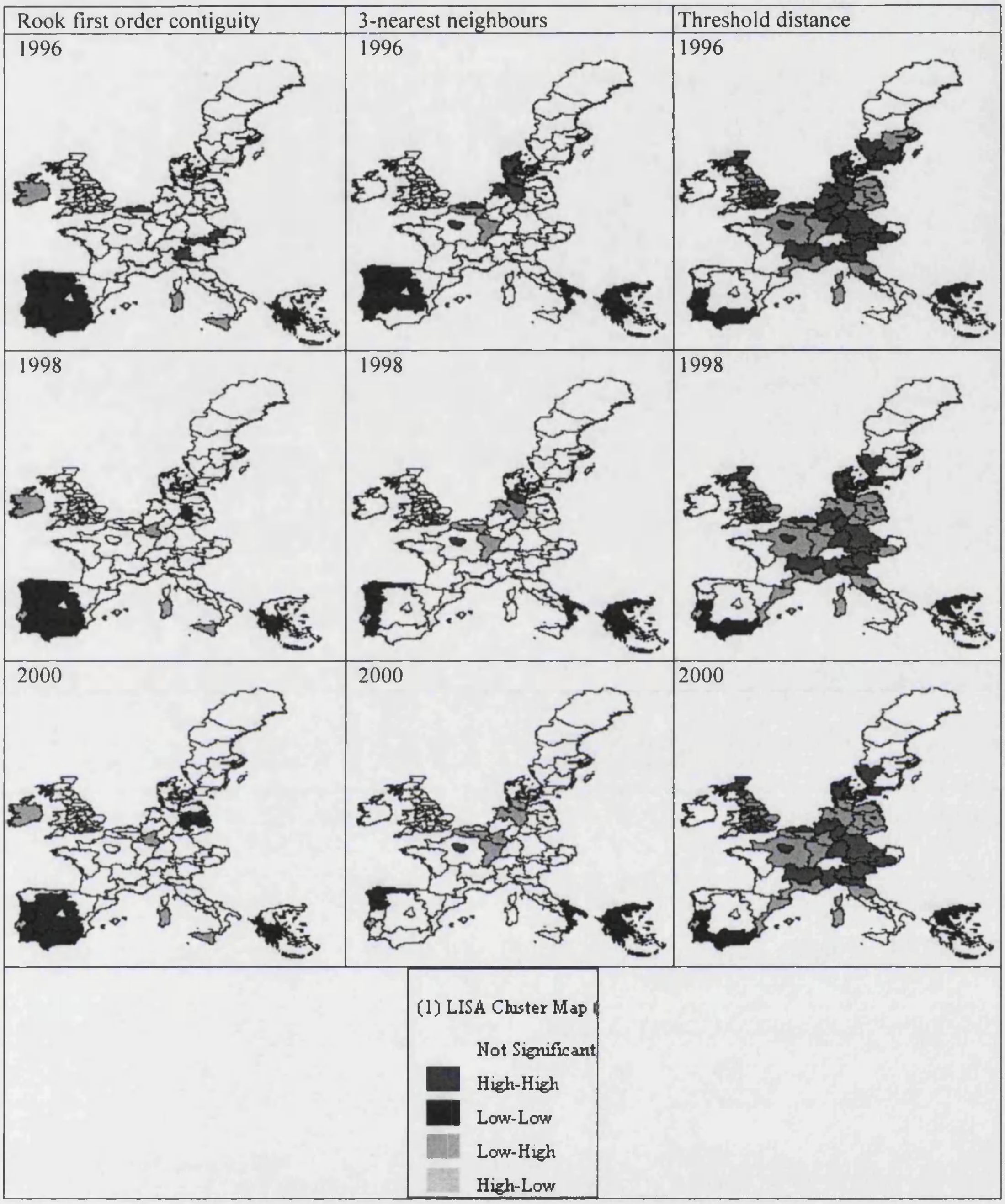
Table 3.4: Moran's I for GDP Per Capita (GDPPC)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.2515	-0.0060	0.0734	3.5082	0.3175	-0.0103	0.0693	4.7302	0.1429	-0.0102	0.0225	6.8044
	1996	0.2428	-0.0114	0.0709	3.5853	0.3053	-0.0055	0.0705	4.4085	0.1426	-0.0101	0.0214	7.1355
	1997	0.2264	-0.0092	0.0728	3.2363	0.2823	-0.0097	0.0732	3.9891	0.1322	-0.0098	0.0227	6.2555
	1998	0.2174	-0.0088	0.0739	3.0609	0.2731	-0.0118	0.0773	3.6856	0.1120	-0.0108	0.0229	5.3624
	1999	0.2025	-0.0095	0.0720	2.9444	0.2478	-0.0100	0.0708	3.6412	0.0963	-0.0083	0.0232	4.5086
	2000	0.1981	-0.0094	0.0738	2.8117	0.2370	-0.0097	0.0729	3.3841	0.0853	-0.0105	0.0219	4.3744
Space-time correlation	1998	0.2310	-0.0126	0.0727	3.3508	0.2890	-0.0091	0.0729	4.0892	0.1268	-0.0102	0.0212	6.4623
	2000	0.2069	-0.0092	0.0733	2.9482	0.2547	-0.0082	0.0698	3.7665	0.0978	-0.0101	0.0229	4.7118

Note: Statistics are significant at the 1% level, except for the space-time correlation for 2000 for the rook first order contiguity, which is significant at the 5% level; E[I]: theoretical mean; Mean: observed mean.

The next step is local spatial autocorrelation analysis. The use of LISA allows one to examine whether there are local spatial clusters of high or low GDP per capita and which regions contribute more to the global spatial autocorrelation. Figure 3.13 displays the cluster maps for output per capita in 1996, 1998 and 2000, which, in particular, show the local variations in spatial autocorrelation of GDP per capita. According to the rook first order contiguity scheme, the German region of Hessen is the centre of a cluster of high output in 1996, while Kentriki Ellada and the Portuguese regions of Centro and Norte are the centres of a cluster of low output in 1996, 1998 and 2000. Additionally, a 'new' poor cluster emerged in 2000 around the east German regions of Sachsen-Anhalt and Brandenburg. The diminishing number of rich clusters over time most probably depicts that the output per head of poorer regions converges towards the EU average. The 3-nearest neighbours weights schemes show that in 1996, 1998 and 2000, Greece, the Italian region of Sud, the Spanish region of Noroeste and the Portuguese region of Norte are clusters for low GDP per capita. Conversely, Île de France, Bedfordshire and Hertfordshire are clusters for high GDP per capita. Finally, considering the threshold distance band, many European regions seem to be sources for rich clusters extending from northern Italy to western Germany, Denmark and southern Sweden. Another cluster includes the southern United Kingdom, eastern Germany, the French regions of Est and Mediterrenee and Central England, include regions in which low GDP per capita is surrounded by areas of high per capita GDP. These regions contribute to the negative spatial autocorrelation.

Figure 3.13: Cluster Map for GDP Per Capita (GDPPC) in 1996, 1998 and 2000



The spatial distribution of GDP per capita exhibits two persistent polarisation patterns: (a) between the rich regions in the north and the poor regions in the south; and (b) between the rich regions in urban areas and the poor regions in rural settings. This evidence can be linked to several regional economic development theories such as the club convergence theories, the cumulative causation theories and the NEG, assuming that natural resources are randomly distributed over the EU. Both the urban-rural divide and the EU north-south divide should be taken into account in the European regional economic process. The economic development of the suburbs is positively related to the development of the central city. For instance, Voith (1998) found that the positive effect of the central city on its suburbs increases with the size of the central city.

3.2.3 The Relationship between Income Per Capita and GDP Per Capita

The relationship between income per capita for the whole population and GDP per capita is explored through a comparison of their boxplots,[39] the spatial distribution of the rate $\frac{Income\ per\ capita}{GDP\ per\ capita}$, the Pearson correlation and the bivariate measures of spatial association.

First, Figure 3.14, which shows the boxplots for income per capita and GDP per capita, is derived from Figure 3.4 and Figure 3.12. That figure shows that GDP per capita is higher than income per capita over the period 1995–2000. Put into context, this is not surprising, since GDP takes into account externalities to physical and human capital (Temple, 1999) and invisible public policies, such as public infrastructure policies, which are not accounted for in income measures. The descriptive statistic analysis also shows that GDP per capita distributions are more skewed than those for income per capita, particularly for 1999 and 2000. However, the lower end of the distributions remained the same between 1996 and 2000.

GDP is a measure of aggregate income on a macro level, through it excludes transfers of income from individuals, companies and government in the form, for example, of social benefits (European Commission, 1999). A region that has a low level of production might have a relatively high level of income due to large social security transfers, but it would still be a less favoured region (European Commission, 2004: 25-26).

There are certain problems encountered in the use of GDP per capita as a measure of income per capita within regions. In city-regions, for example, commuting by people resident in other regions adds to the local workforce and GDP. The city-region's GDP per capita as a measure of income per capita is, therefore, overstated, while that of neighbouring regions is understated (European Commission, 1999). Consequently, the urbanisation degree of a region is likely to be a crucial factor in the distinction between income per capita and GDP per capita.

[39] Since the variables are measured on the same scale and are recorded using the same units (averages), their distributions are compared without any method of standardisation.

Additional problems encountered in the use of GDP per capita as a measure of income per capita within regions are the following:[40]

- GDP counts work that does not produce a net change or that results from repairing harm, such as a natural disaster (i.e. an earthquake).
- Cross-border trade within companies (i.e. to escape high taxation) distorts the GDP. Examples include the German division of Ebay that evades German tax by doing business in Switzerland.
- If a region does not spend, but saves and invests in other regions, its GDP will decline in comparison to a region that spends borrowed money.

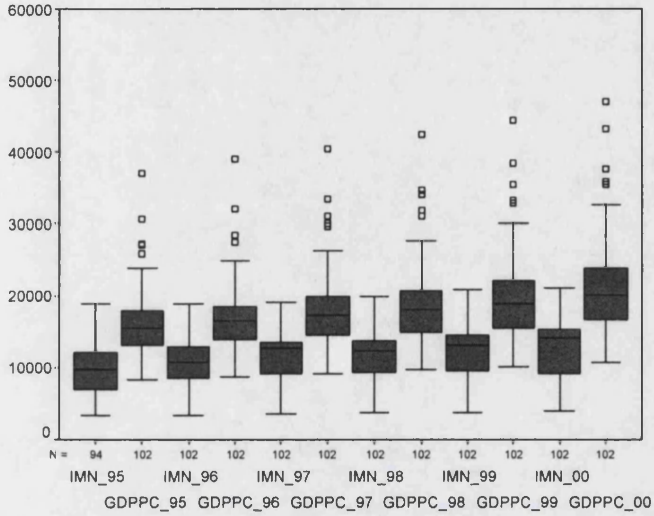
Another problem encountered in using GDP per capita as a measure of the size and performance of a regional economy is that GDP does not include deductions for depreciation of physical capital or depletion and degradation of natural resources.[41]

Generally, GDP per capita is a measure of production where it is generated, while income per capita concerns a population in their place of residence. Therefore, income per capita is a 'better' indicator of regional performance. Income per capita might also be a 'better' proxy for standard of living in a regional economy.

[40] http://en.wikipedia.org/wiki/GDP.

[41] www.undp.org/hdr2001/ — United Nations Development Programme.

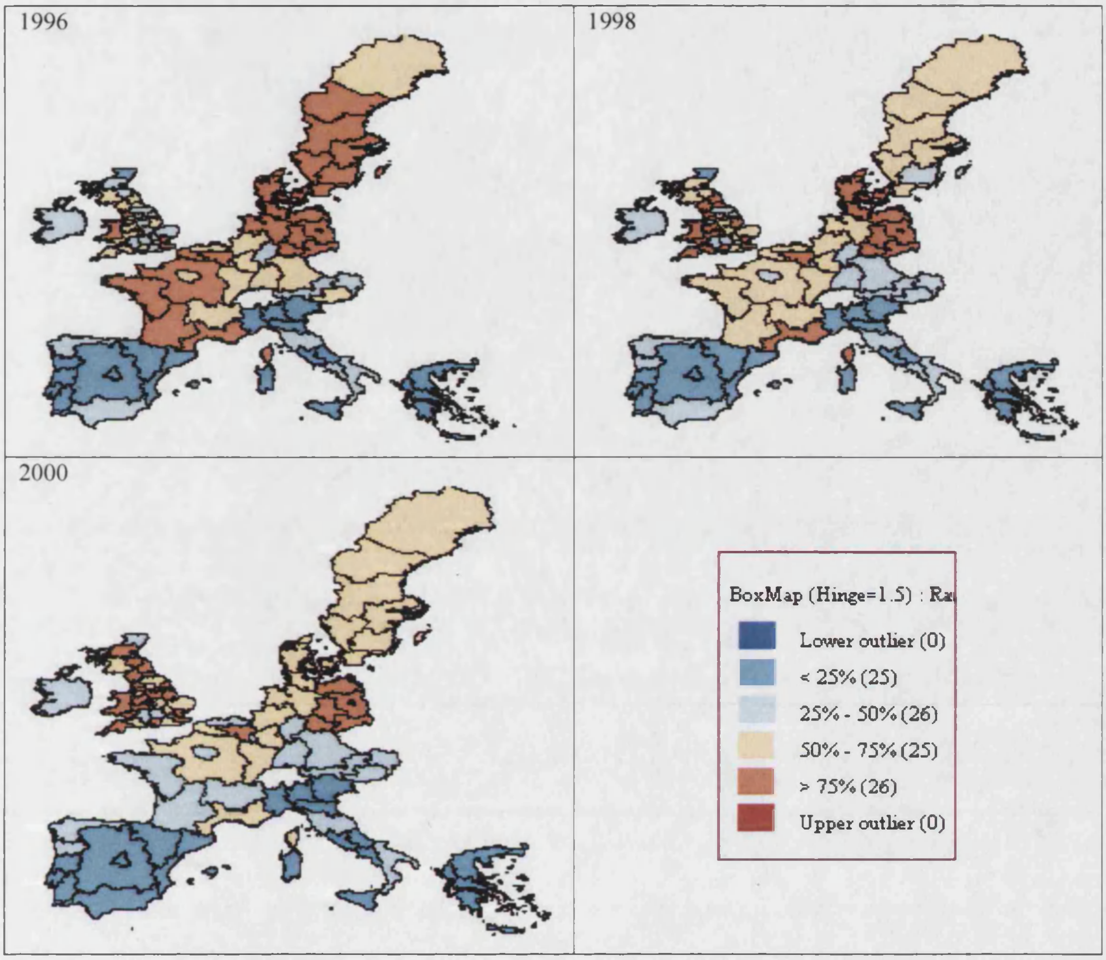
Figure 3.14: Boxplot for Income Per Capita of the Population as a Whole (IMN) and GDP Per Capita (GDPPC)



Note: extreme cases and outliers are sorted in descending order: BE1, DE6, LU, FR1 and UK55 in 1995, 1996 and 1997; BE1, DE6, LU, UK55 and FR1 in 1998; BE1, LU, DE6, UK55 and FR1 in 1999 and 2000 (see Appendix A1.1).

Second, the spatial distribution of income per capita over GDP per capita within a region is presented using a choropleth map. Figure 3.15 is a special case of a quartile map, in which the outliers are shaded differently (Anselin, 1994). The higher the rate, the lower the differences between GDP and income per capita. This rate is expected to be lower than one. However, it is higher than one for Kent in 1998, and for Kent, Essex, Lancashire and Clwyd, Dyfed, Gwynedd and Powys in 2000. In those regions, GDP per capita is probably lower than income per capita due to the low investments in public infrastructure or to the large social security transfers. As is shown in the figure, Spain, Greece, Italy, Ireland and eastern Germany register higher differences than the remaining European regions. In Cohesion countries, GDP per capita is much higher than income per capita, probably due to the impact of Structural Funds. The differences increased slightly between 1996 and 2000 in all but the United Kingdom regions.

Figure 3.15: Spatial Distribution of Income Per capita for the Population as a Whole (IMN) over GDP Per Capita (GDPPC) in 1996, 1998 and 2000



Third, the short evolution of the Pearson correlation between income per capita and GDP per capita from 1995 to 2000 registers a slight decrease. For example, the Pearson correlation is 0.645 in 1996, 0.621 in 1998 and 0.536 in 2000.[42]

Fourth, the bivariate measure of spatial correlation is explored. This measure relates GDP per capita in a region to income per capita in neighbouring regions, and vice versa. The correlation between a region's income per capita and the GDP per capita of neighbouring regions is 0.219 for 1996; 0.212 for 1998; and 0.183 for 2000 (for the rook first order contiguity spatial weights matrix). Conversely, the correlation between a region's GDP per capita and the income per capita of neighbouring regions is 0.272 for 1996; 0.238 for 1998; and 0.193 for 2000. To sum up, although the correlation between

[42] These correlations are significant at the 0.01 level (2-tailed) with standard error 0.000.

GDP per capita and income per capita is high, income per capita is a 'better' indicator of regional performance.

3.3 Defining Income Inequality

This section provides a definition of income inequality and an indication of how inequality is measured. Two fundamental issues encountered in measuring income inequality are connected to the units of analysis and the weighting of units (or lack of it) by their population size. The answers depend on the research design and the research question. First, the basic units used to measure income inequalities might be either individuals or territorial units, which mean groups of individuals such as regions or countries. Sala-i-Martin (2003) states that it is admissible to use territorial units when one sets out to test theories or to examine government policies that relate to countries or regions, while it is relevant to use individuals when one is interested in the welfare of people. It has already been stated that this research investigates the evolution of income inequalities within regions in the EU and focuses on the welfare of people. Therefore, in accordance with Sala-i-Martin, it is appropriate to use individuals as basic units to measure income inequalities. Second, in the case of groups of individuals, one crucial issue is whether one should weight regions by their population size. Firebaugh (2003) argues that if the goal is to test a theory of how regional economies work — so each region can be viewed as a separate realisation of certain underlying economic processes — then each region would be weighted the same; whereas, if the goal is to calculate the average disproportionality of individuals' income ratios there is no reason why individuals in large regions should carry less weight than individuals in small regions. Consequently, this research is based on weighted inequality indices in order to decompose, for example, the generalised entropy indices. When the basic units are individuals, they are the same size, so they are weighted equally.

This section examines income inequality and consists of three subsections. The first subsection looks at income inequality as average disproportionality, the second analyses the criteria for evaluating income inequality and the last describes the four most well-known indicators.

3.3.1 Inequality as Average Disproportionality

Although the term income inequality is widely used, there is sometimes confusion over what the term 'inequality' exactly means. Before examining the definition of income inequality, it is important to stress first that inequality is not synonymous with inequity, which explicitly invokes norms; and second that inequality is based on ratios and not on gaps (Firebaugh, 2003). Moreover, it is important to distinguish between income inequality and poverty. Poverty is the fraction of the distribution of income that lies below a commonly accepted poverty line (Cowell, 1995; Sala-i-Martin, 2002). Ravallion (1997a; 1997b), Ravallion and Chen (2003) and Justino et al. (2004) have shown that a large number of individuals remain poor, not because they live in poor regions (i.e. countries) but because high levels of income inequality create exclusion and persistent poverty among certain population groups.

In the literature on inequality, it is conceptualised as the average disproportionality. Inequality concerns a 'disproportionate share', which means a share that is bigger or smaller than the average share of all basic units. The challenge of income inequality literature is to comprehend how to aggregate those basic unit disproportionalities to obtain a measure of overall income inequality. Since each region has a different distribution of income, an index of income inequality that is comparable across regions has to be compiled. The index should be fundamentally based on the principle that income inequality increases as the income ratios increasingly deviate from 1.0. Hence, the task in hand is to devise summary measures of income inequality that distinguish more inequality from less inequality (Firebaugh, 2003). I express income inequality indices in a general form as disproportionality functions.

Consider a population of basic units $i \in \{1,2,...,N\}$, where each unit is associated with a unique value of the measured income y such that $\sum_{i=1}^{N} y_i \equiv Y$. Thus y_i is income share, that is unit i's total income (individual or group of individuals) as a proportion of the total income for the entire population. I define the income ratio r_i as the ratio of y_i to the average $\overline{Y}$ ($\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} y_i = \frac{Y}{N}$)

$$r_i = y_i / \overline{Y}$$

By definition, equality exists when income is equally distributed across all units. Inequality is zero when and only when $r_i = 1.0$ for all of i; otherwise, inequality is greater than zero. When the basic units are individuals, the units are the same size, so they are weighted equally. Income inequality remains constant when income grows at the same rate for every person over time. In contrast, income gaps widen among people when income changes at the same rate for all persons. Firebaugh (2003: 73) points out that since we live in a world where the average income has been doubling every half century or less, the gap between richer and poorer nations naturally will widen (as well as the gap between richer and poorer persons), irrespective of any change in the degree of income inequality across nations (as well as across individuals).

Conceptualising inequality as the average disproportionality across all basic units implies that the degree of income inequality depends on the average distance of the income ratios r_i from 1.0. Income inequality is unaffected by proportional increases or decreases. Inequality indices I can be expressed in a common form

$$I = \frac{1}{N}\sum_{i=1}^{N} f(r_i),$$

where f denotes the disproportionality or distance function which captures the mathematical functions for determining deviations of income ratios from 1.0.

In the general case, where units differ in size, as is the case when basic units denote regions and thus population varies across regions, an inequality index is

$$I = \sum_i p_i f(r_i),$$

where p_i denotes population share and defines as n_i / N.

Generally,

$$p_i = \begin{cases} 1/N & \textit{for unweighted index} \\ w_i & \textit{for weighted index} \end{cases}$$

If the basic units are individuals, the unweighted index equalises the weighted index. The inequality index is expressed in a common form as a function of income ratios r_i and population shares p_i. If, for example, the population share is constant, inequality indices differ only because they employ different distance functions of the income ratios. A region's contribution in terms of income inequality depends on the region's income ratio and population share, while an individual's contribution to income inequality depends only on his/her income ratio. It follows that the evolution of a region's contribution to change in interregional inequality is determined by the change in both the region's income ratio and the region's population share, whereas the evolution of inequality using individuals as basic units depends on the change in individual's income ratio alone .

Income inequality can occur at different levels of aggregation. For example, the income inequality for Europe may vary across individuals, across regions and across nations. Equality at a higher level of aggregation does not necessarily imply equality at a lower level (Firebaugh, 2003). What is true on a certain spatial scale is not necessarily true on another that incurs the 'ecological fallacy' and the 'modifiable areal unit problem' (Fujita and Thisse, 2002). From a methodological standpoint, most quantitative research purporting to support the income inequality research is potentially compromised by a problem that is known as 'ecological bias', which arises when correlations identified in aggregated data differ from the underlying correlations that would be observed if one were examining individual data (Eberstadt and Satel, 2004: 14).

3.3.2 Criteria for Evaluating Income Inequality

Cowell and Amiel (1999) argue that, in economic terms, the question 'what is inequality?' is transformed into the question 'how are inequality comparisons to be made?'. They stress that the meaning of income inequality comparisons depends critically upon the axiomatic basis that is specified for the inequality comparison rule. The four principles of crucial importance are: the principle of income scale independence, the principle of population size independence, the principle of decomposability and the principle of transfer (Allison, 1978; Cowell, 1995; Cowell and Amiel, 1999; Firebaugh, 2003). All these principles are criteria that must be satisfied by inequality measures (Cowell, 1995: 54).

Scale or mean independence: If all incomes double for a fixed population, the average income is also doubled, but the income ratio remains the same. The relative differences among units have not been changed. Thus income inequality is scale or mean independent when income is increased or reduced at the same rate for everyone. Cowell (1995: 36) states, '*the measured inequality of the slices of the cake should not depend on the size of the cake*'. A measure should be robust to the chosen income scale. Hence a measure is scale invariant when it responds to relative rather than to absolute differences (Blau, 1977a; Allison, 1978).

Population size independence: If one measures the inequality of a particular economy with n persons and then merges it with another group of n persons, which has the same level of measured inequality, the resulting income inequality measure should remain the same. Cowell (1995: 36) emphasises that '... *inequality of the cake distribution should not depend on the number of cake-receivers*'.

Additive decomposability: If everyone in the population is sorted into mutually exclusive groups, such as population subgroups (i.e. nations or regions) or factor components (i.e. age groups or urbanisation level), I construct an additively decomposable index in which the index value for all inequality is a weighted sum of the within-group index value and the between-group index value (Firebaugh, 2003: 79). The between-group component of inequality is found simply by assuming that everyone within a group receives that group's mean income (i.e. the region's mean income),[43] and the within-group inequality is a weighted average of inequality in each subgroup although the weights do not necessarily add up to one (Cowell, 1995: 151).

Principle of transfers: The transfer principle states that for any given income distribution, if one takes a small amount of income from one person and gives it to a richer person then income inequality must increase. This principle was originally introduced by Pigou (1912) and Dalton (1920) and is known as Pigou-Dalton condition. However, there are significant differences in sensitivity to transfers at different points on the scale (Atkinson, 1970). An index is, for example, equally sensitive to transfers at all income levels, when a transfer of £100 from a person earning £5,000 to another earning £6,000 has the same impact as a transfer of the same amount from a person earning £50,000 to another earning £51,000 (Allison, 1978). In both cases the distance between the two people's income level is the same (£51,000–£50,000 = £6,000–£5,000). However, income transfers at higher levels of income are less significant than the same transfer at lower levels of income (Firebaugh, 2003: 80). For instance, £1,000 means more to a poor person than it does to a rich one. Thus, income increases at the lower end of the scale produce greater welfare benefits than do income increases at the upper end of the income distribution (Firebaugh, 1999: 1619). The sensitivity to transfers is linked to the welfare principle. Income inequality satisfies the welfare principle when it is more sensitive to transfers among lower incomes and less sensitive to transfers among the recipients of the top incomes (Allison, 1978).

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[43] Hence, the between-group component of inequality is independent of redistribution within any of the groups (Cowell, 1995: 151).

3.3.3 *Inequality Indices*

There are several indices for measuring income inequalities. Different indices yield somewhat different estimates of income inequality, because they use a different distance function. The four most well-known indicators of income inequality are: the relative mean deviation index, the Gini index, the generalised entropy index and the Atkinson index.

3.3.3.1 The Relative Mean Deviation Index

The relative mean deviation index (RMD) is defined as

$$RMD = \sum_i p_i |r_i - 1|$$

The disproportionality function of the relative mean deviation index is

$$f(r_i) = |r_i - 1|$$

When the basic units are individuals, its minimum value is 0 for perfect equality and its maximum value is $2\left(1 - \frac{1}{N}\right)$ for perfect inequality. The upper limit of the relative mean deviation index approaches 2 as N increases.

The relative mean deviation index is independent of income scale and population size, but does not obey the principle of transfers, since a rich-to-poor transfer may leave income inequality unchanged rather than reducing it (Cowell, 1995). According to Schwartz and Winship (1979), the relative mean deviation index may be used to measure the degree of segregation, in which case it is known as an index of dissimilarity.

3.3.3.2 Gini Index

Following Cowell (1995), the Gini index (G or $GINI$) or the Gini coefficient is computed as follows

$$G = \frac{1}{2N^2\overline{Y}} \sum_{i=1}^{N} \sum_{j=1}^{N} |y_i - y_j| \text{ or}$$

$$G = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} |r_i - r_j| / 2$$

The Gini index is one-half of the average distance between the income ratios for all pairs of individuals. Two individuals are randomly selected with replacement from the entire population; one-half of the distance between the individuals' income ratios is calculated, the process is repeated M times, and the average taken (Firebaugh, 2003). Each individual has the probability $1/N$ of being selected. The above index is an unweighted index. When the basic units are individuals, it is also a weighted index. The Gini index varies from 0 for perfect equality to $\frac{N-1}{N}$ for perfect inequality. The upper limit of the Gini index approaches 1.0 as N increases.

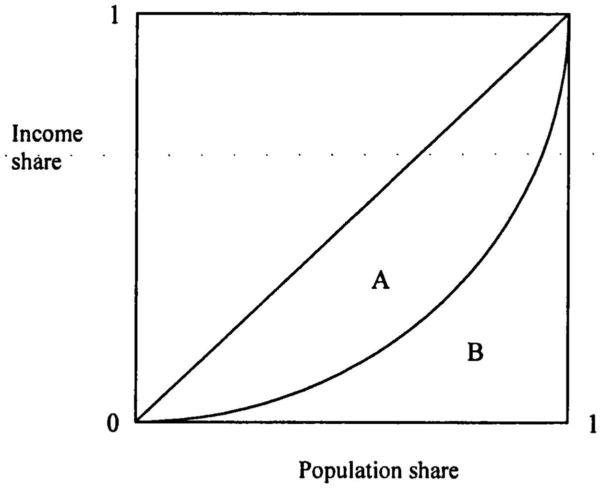
Shankar and Shah (2003), following Kakwani and World Bank (1980), computed the weighted Gini index G_w as

$$G_w = \frac{1}{2\overline{Y}}\sum_i \sum_j |y_i - y_j| p_i p_j \text{ or}$$

$$G_w = \frac{1}{2}\sum_i \sum_j |r_i - r_j| p_i p_j$$

One way of viewing the Gini index is in terms of a Lorenz curve (Sen, 1997; Sen and Foster, 1997). It can help one to explain the concept more clearly (Lui, 1997). I arrange the population in ascending order of income and calculate the accumulated income share for each observation. Then, I plot individuals as shown in Figure 3.16, with the population share as the horizontal axis and the cumulative income share as the vertical axis (Lui, 1997).

Figure 3.16: The Lorenz Curve



Generally speaking, a more shallow curve reflects greater income inequality. The Gini coefficient is also defined as

$$G = \frac{Area(A)}{Area(A) + Area(B)}$$

For perfectly equal income distribution, there would be no area between the 45 degree line and the Lorenz curve ($Area(A) = 0$), while for complete inequality, the Lorenz curve would coincide with the straight lines at the lower and right boundaries of the curve ($Area(B) = 0$).

Following Allison (1978), the Gini index for grouped data is

$$G = \sum_i p_i r_i (q_i - Q_i),$$

where q_i is the proportion of the total population in units poorer than unit i and Q_i is the proportion of the total population in units richer than unit i.

The disproportionality function of the Gini index is

$$f(r_i) = r_i (q_i - Q_i)$$

The Gini index is an appropriate specification of what Blau (1977a; 1977b) conceptualises as inequality. He argues that inequality is a fundamental characteristic of all graduated social parameters and it is defined as the average status between any two pairs relative to the average status.

The Gini index is the most popular measure of income inequality. However, it has some limitations. Although it satisfies the principle of transfers (Cowell, 1995), it is not consistent with the welfare principle that income transfers are more consequential among the poor than among the rich (Firebaugh, 2003). In addition, it is not additively decomposable (Bourguignon, 1979). From technical point of view, it is harder to calculate than most other measures. One underpinning characteristic of the Gini index is that it provides non-redundant information about income inequality, because it is relatively more sensitive to change around the median of the income distribution and less sensitive to transfers among the very rich or the very poor (Allison, 1978; Firebaugh, 2003). Hence the Gini forms are acceptable to test theories regarding the relationship between national income inequalities and economic growth such as political economy models.

3.3.3.3 The Generalised Entropy Index

The generalised entropy index (GE) is defined as

$$GE(a) = \frac{1}{N}\frac{1}{a(a-1)}\sum_{i=1}^{N}(r_i^a - 1),$$

where a is a sensitive parameter which measures the weight given to distances among values taken by y at different parts of the distribution of y (Brülhart and Traeger, 2005).

The distance function of the generalised entropy index is

$$f(r_i) = \frac{1}{a(a-1)}(r_i^a - 1)$$

The generalised entropy index is decomposable by population subgroups. I define an exhaustive partition of the population of basic units $i \in \{1,2,...,N\}$ into mutually exclusive subgroups of basic units $j \in \{1,2,...,L\}$, such as regions. This index can be decomposed additively as:

$$GE(a) = GE_b(a) + GE_w(a),$$

where $GE_b(a)$ and $GE_w(a)$ stand for the between-subgroups and the within-subgroups of the generalised entropy index, respectively.

1. The Theil Index

The case where $a = 1$ yields the Theil index (T or $GE1$) of inequality (Theil, 1967; Brülhart and Traeger, 2005). The Theil index is defined as

$T = \sum_i p_i r_i \log(r_i)$[44] or

$$T = \sum_i y_i \log(y_i / p_i)$$

The disproportionality function of the Theil index is defined by the following expression

[44] The Theil index can be defined using logarithms to any base. I use the natural logarithm for simplicity throughout my empirical research.

$f(r_i) = r_i \log(r_i)$

The Theil minimum value is 0 for perfect equality and its maximum value is logN.

Consider the following two-level hierarchical structure of the EU: region–individual. Using the mutually exclusive subgroups of basic units, the overall level of income inequality can be measured using the following Theil index

$$T = \sum_j \sum_i p_{ji} r_{ji} \log(r_{ji}),$$

where p_{ji} denotes population share, defined as n_{ji} / N (where n_{ji} is the weight of individual i in region j and N is the total population of all individuals such that $N = \sum_j \sum_i N_{ji}$), and r_{ji} is the income ratio of individual i in region j.

Thus, the Theil index (i.e. country inequality) can be decomposed additively as

$$T = \sum_j p_j r_j \log(r_j) + \sum_j p_j r_j T_j \text{ or}$$

$$T = \sum_j y_j \log(y_j / p_j) + \sum_j y_j T_j ,$$

where $\sum_j p_j r_j \log(r_j)$ and $\sum_j p_j r_j T_j$ are the measures of between-region and the within-region inequality, respectively. The between-regions component in the inequality identity is a population-weighted component that assumes that everyone within a region receives that region's mean income. This component shows the degree to which the levels of income converge with one another. The within-regions component in the inequality identity is a weighted average for each individual, where the weights add up to one. This component emphasises the disparities within regions.

Following Akita (2003), I decompose the overall income inequality of the Theil index into three components. Now, consider the following hierarchical structure of the EU: country–region–individual. It is an extension of the two-level Theil decomposition method. This method is analogous to a two-stage nested design in the analysis of variance (Montgomery, 1984; Akita, 2003). In this case, the regions $j \in \{1,2,...,L\}$ are mutually exclusive subgroups of countries $k \in \{1,2,...,M\}$. The Theil index (i.e. EU inequality) is defined as

$$T = \sum_k \sum_j \sum_i p_{kji} r_{kji} \log(r_{kji}),$$

where p_{kji} denotes population share, defined as n_{kji} / N (where n_{kji} is the weight of individual i in region j in country k and N is the total population of all individuals such that $N = \sum_k \sum_j \sum_i N_{kji}$), and r_{kji} is the income ratio of individual i in region j in country k.

The Theil index can be decomposed additively as

$$T = \sum_k \sum_j p_{kj} r_{kj} T_{kj} + \sum_k p_k r_k T_k + \sum_k p_k r_k \log(r_k) \text{ or}$$

$$T = \sum_k \sum_j y_{kj} T_{kj} + \sum_k y_k T_k + \sum_k y_k \log(y_k / p_k)$$

where $\sum_k \sum_j p_{kj} r_{kj} T_{kj}$ is the within-region income inequality, $\sum_k p_k r_k T_k$ is the between-region and the within-country income inequality and $\sum_k p_k r_k \log(r_k)$ is the between-country income inequality (or the European income inequality using countries as basic units). The within country inequality is a weighted average of inequality in each region and the component weights add up to one.

The Theil index satisfies all the criteria of income inequality indices. It is income scale and population size invariant, additively decomposable and satisfies both the principle of transfers and the welfare principle. The relative sensitivities of the Theil index to population change and income change hold for within-region income as well as for the between-region inequalities (Firebaugh, 1999). Change depends on the ratio of incomes. Allison (1978) observes, for example, that transferring £100 from a person earning £5,000 to a person earning £6,000 has approximately the same effect on the Theil index as a transfer of the same amount from a person earning £50,000 to another earning £60,000.[45] He summarises that the lower the level of income, the more sensitive the Theil index is to transfers.

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[45] This is because in Theil index transfer $i \rightarrow j$ is $\frac{1}{N\bar{Y}} \log\left(\frac{y_j}{y_i}\right)$ (Cowell, 1995: 140).

2. The Squared Coefficient of Variation

Variance (VAR) is the most common statistical measure of dispersion for a distribution. The distance concept of variance is that of absolute differences. Variance is defined as

$$VAR = \sum_i p_i (y_i - \overline{Y})^2$$

This index is sensitive to extreme observations. Additionally, the variance is not scale independent. Conversely, the squared coefficient of variation (SCV or $GE2$) is scale independent, because it concentrates on relative variation. In a generalised entropy index, when the parameter $a = 2$, this index yields the squared coefficient of variation index (Sala-i-Martin, 2002; Brülhart and Traeger, 2005).

The squared coefficient of variation is obtained by dividing the variance by the squared mean $\overline{Y}$. It is given by the following expression

$$SCV = \sum_i p_i (r_i - 1)^2$$ [46]

The disproportionality function of the squared coefficient of variation is

$$f(r_i) = (r_i - 1)^2$$

The squared coefficient of variation varies from 0 for perfect equality to $N-1$ for perfect inequality.

3.3.3.4 The Atkinson Index

The Atkinson (1970) index (A) is defined as

$$A = 1 - \left(\sum_i p_i r_i^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}},$$

[46] More explicitly,

$$SCV = \frac{VAR}{\overline{X}^2} = \frac{\sum_i p_i (r_i \overline{X} - \overline{X})^2}{\overline{X}^2} = \sum_i p_i (r_i - 1)^2$$

where the parameter ε ($\varepsilon > 0$) denotes the relative sensitivity of the Atkinson index to transfers at different points in the income distribution.

Thus, the larger the parameter ε, the greater the weight given to the lower end of the income distribution (Firebaugh, 1999: 1619). To put this in a slightly different way, as the parameter rises, the Atkinson index becomes more sensitive to transfers among those on lower incomes and less sensitive to transfers among the top income recipients (Allison, 1978). The distance concept of the Atkinson index is measured in terms of the difference in marginal social utilities (Cowell, 1995). The Atkinson index is independent of income scale and population size and the between-group and within-group components do not add up exactly to the total inequality (Cowell, 1995). Finally, the Atkinson index varies from 0 for perfect equality to $1 - N^{-\varepsilon/1-\varepsilon}$. The upper limit of the Atkinson index approaches 1.0 as N increases.

3.4 Measuring Income Inequality within and between Regions in Europe

This section concerns the measurement of income inequality at different spatial levels (European, country and regional) and using different units of analysis, which means at different levels of spatial resolution (country, region, individual). It also looks at the spatial distribution of income inequality in order to examine whether income inequality tends to be geographically clustered. Income inequality is measured by the regionalised microeconomic variable '*Total net personal income (detailed, NC, total year prior to the survey)*' which is extracted from the ECHP dataset. The section consists of three subsections. The first and second subsections describe the income inequality indices used within European regions for the whole of the population and for normally working people, respectively. They also exhibit the linear correlation among inequality indices and illustrate the spatial dependence analysis. The third subsection decomposes the European income inequality by population sub-groups in order to find the percentage of European income inequality that can explained in terms of between-region and the within-region income inequality.

3.4.1 Within-region Income Inequality for the Population as a Whole

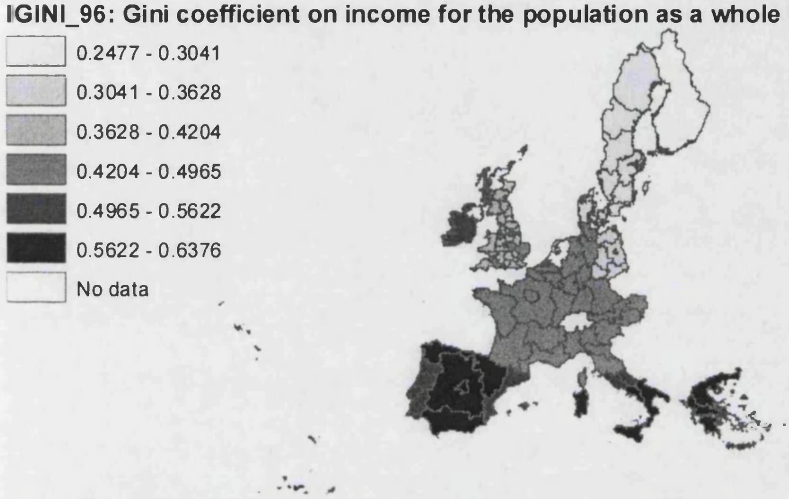
Income inequality within regions is measured by the relative mean deviation index ($IRMD$), the Gini index ($IGINI$), the generalised entropy index for two different parameters ($IGE1$ when $a = 1$, and $IGE2$ when $a = 2$) and the Atkinson index for three parameters ($IA025$ when $\varepsilon = 0.25$, $IA050$ when $\varepsilon = 0.50$ and $\varepsilon = 0.75$ when $IA075$). The initial step of ESDA is to map income inequality indices in order to see whether they are randomly distributed over the EU or whether there are similarities between regions. The values from the income inequality indices are divided into six categories according to Jenk's classification. The next step is to use the univariate boxplot technique in order to show the shape of the inequality distribution, its central value and the variability. The Pearson correlation index is also presented as a way to measure the lineal correlation among indices. Finally, the role of spatial effects is described.

Mapping the Gini coefficient (Figure 3.17), it is shown that there are prominent differences in income inequality within regions between different parts of Europe, predominantly between the northern and southern areas of Europe. Income inequality is greater in the southern periphery, extending from Greece to southern Italy (Lazio, Sicilia, Sud, Campania and Sardinia) and western Spain (Canarias, Sur, Centro and Noroeste) over the period 1996–2000. By contrast, northern Europe (Sweden, Denmark and the southern United Kingdom) has the lowest level of income inequality, with the exception of Ireland. The findings show that the between-region and within-country income inequalities are lower than the between-country inequalities. Nevertheless, income inequality within German regions is lower in the east (Mecklenburg-Vorpommern, Brandenburg, Sachsen, Sachsen-Anhalt and Thüringen) than in the west, demonstrating a German east-west divide. Additionally, the results show an Italian north-south divide. Italian income inequality is higher in the south than in the north. Looking at 1996, for example, it is clear that income inequality was higher in the southern periphery than in central Europe, which, in turn, was higher than in northern Europe (Denmark and Sweden). Looking at 1998 and 2000, income inequality appears to have been more randomly distributed in central Europe. To sum up, the spatial distributions presented here show that there are disparities in income inequality within regions between different parts of Europe, particularly between the south, the centre and the north of Europe.

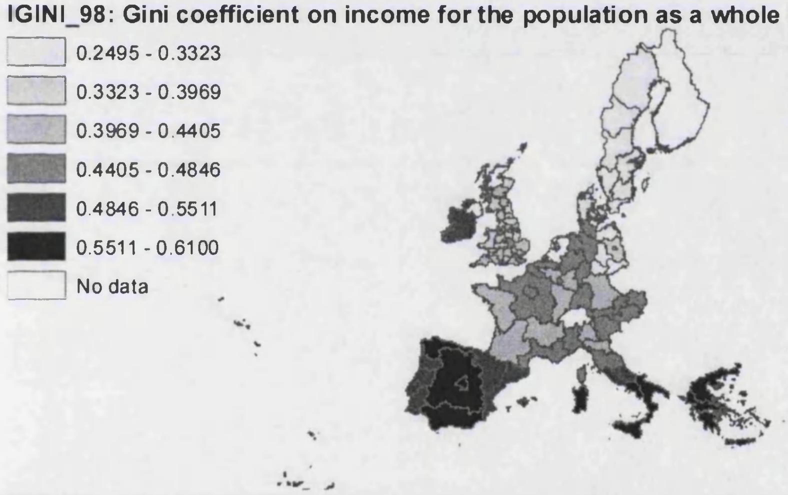
The geographical distributions of other measures of inequality such as the relative mean deviation index, the Theil index, the squared coefficient of variation and the Atkinson index yield similar results.[47]

Figure 3.17: Spatial Distribution of the Gini Coefficient on Income (IGINI) in 1996, 1998 and 2000

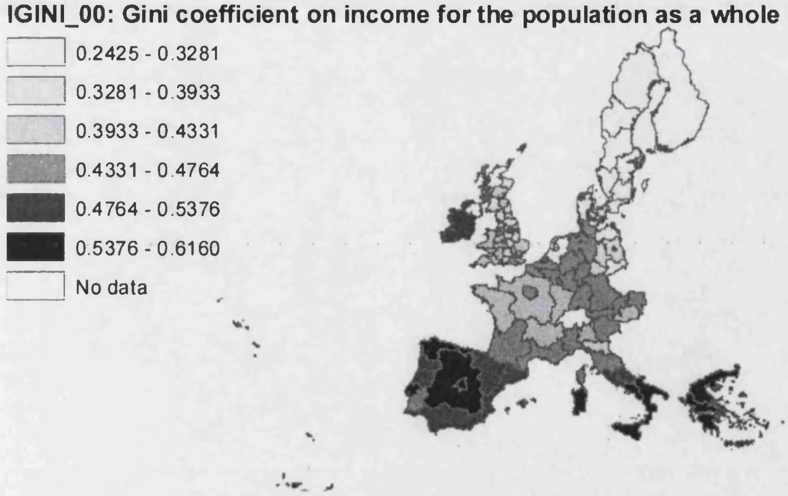
IGINI_96: Gini coefficient on income for the population as a whole in 1996



IGINI_98: Gini coefficient on income for the population as a whole in 1998



IGINI_00: Gini coefficient on income for the population as a whole in 2000



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[47] The results will be provided on request.

Looking at the univariate boxplot for the Gini coefficient (Figure 3.18), Sicilia represents the upper outlier in 1997 and 2000, while Mellestra Norrland and Norra Mellansverige, and Övre Norrland are the lower outliers in 1998 and 2000, respectively. Furthermore, the whisker and box length are wider in 1996, whereas they are narrower in 2000. Generally, the distribution of the Gini coefficient is quite compact, accepts the normality assumption and indicates a right tail between 1995 and 1999 and a left tail in 2000.[48] Analysing the boxplot for the Theil index, only Sicilia differs from the median by more than the interquartile range times 1.5 in the higher end of the distribution, in 1997 and 2000. In 1996, 1998 and 2000 the distribution is fairly compact, because the whiskers are in fact the extreme values. Conversely, exploring the boxplot for the squared coefficient of variation, the distribution is skewed, but much of the skewness is due to the outliers and the extreme values in the higher end of the distribution, such as Île de France and Vlaams Gewest. Although many European regions are among the outliers from the upper edge of the box, none of the values is more than 1.5 box lengths from the lower edge of the box. In all boxplots, the mean is greater than the median, because the mean is 'pulled' towards the longest tail of the distribution. The univariate boxplot of the relative mean deviation index for the European regions between 1996 and 2000 shows that there are many outliers. The northern Italian regions Campania, Sud, Sicilia and Sardinia, the Greek region Voreia Ellada (in 1998) and the Spanish region Centro (in 2000) are the outliers from the upper edge of the boxplot, while the Swedish regions Norra Mellansverige, Mellersta Norrland and Övre Norrland (in 1998 and 2000) are the outliers from the lower edge. Additionally, the differences between the two whiskers decreased slightly from 1996 to 2000. Finally, the boxplots of the Atkinson index demonstrate that, from 1996 to 1998, the distribution was fairly compact, and, in 1999 and 2000, Sicilia was the upper outlier.

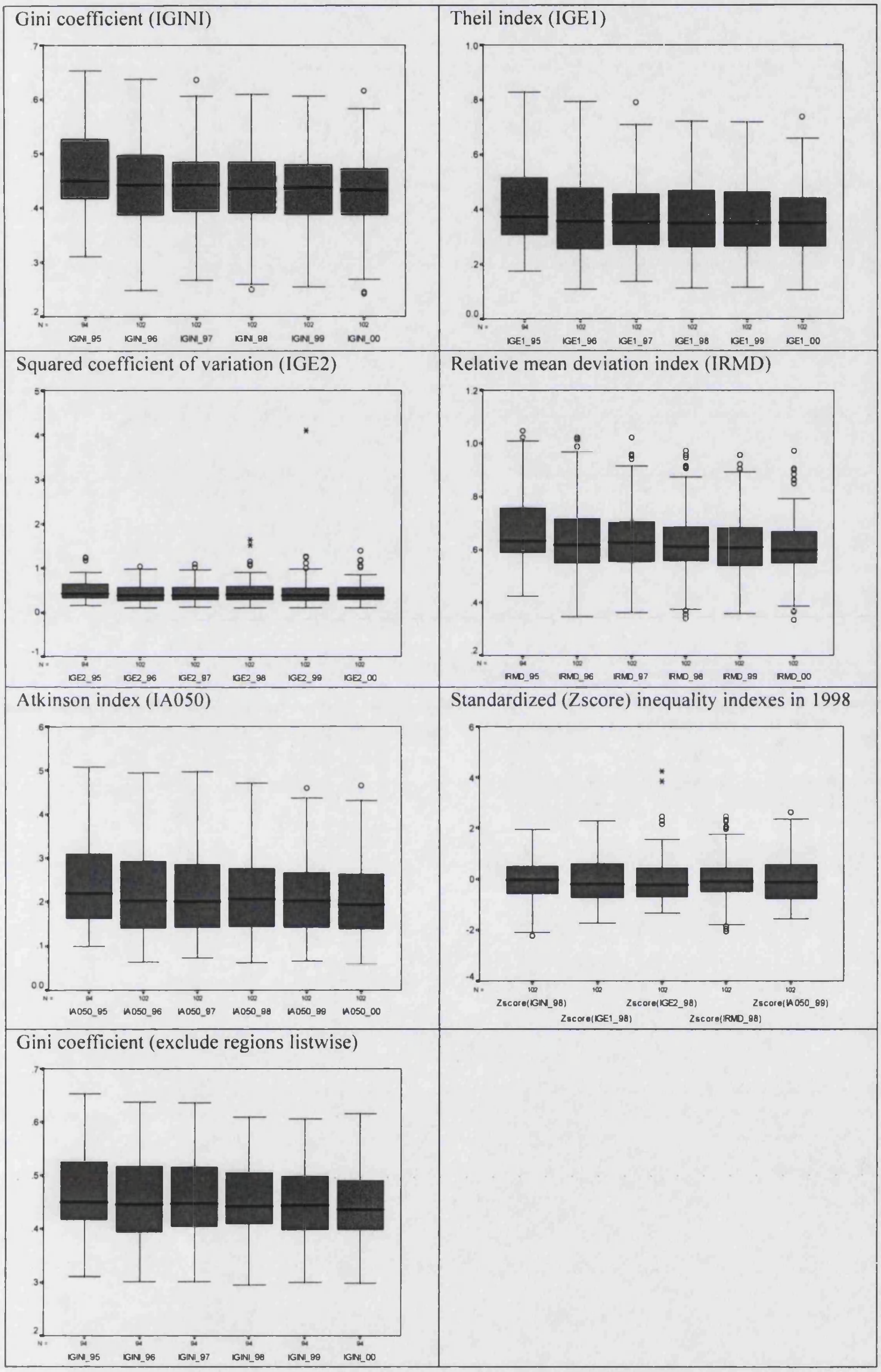
Income inequality distributions are comparable only when they are measured on the same scale. All indices have been standardised to have zero mean and unit variance Representing the boxplots for the standardised income inequality indices in 1998, for example (Figure 3.18), it is shown that they are quite similar to one another except for the squared coefficient of variation. In 1998, the normality assumption is accepted for

[48] The ratio of skewness to standard error is 1.81 in 1995, 1.88 in 1996, 0.70 in 1997, 0.01 in 1998, 0.05 in 1999 and -0.05 in 2000.

the Gini and the relative mean deviation index, and is rejected for the generalised entropy indices and the Atkinson index.[49]

[49] The ratio of skewness to standard error is 0.08 for the Gini coefficient, 2.23 for the Theil index, 7.09 for the squared coefficient of variation, 1.44 for the relative mean deviation index and 2.90 for the Atkinson index for 1998.

Figure 3.18: Boxplot for Income Inequality Indices



Note: extreme cases and outliers are sorted in descending order:
IGINI: ITA (upper end) in 1997; SE07 (lower end) in 1998; ITA (upper end) and SE09 and SE08 (lower end) in 2000.
IGE1: ITA (upper end) in 1997 and 2000.

IGE2: BE1, ES4 and ES1 (upper end) in 1995; IE (upper end) in 1996; BE1 and GR3 (upper end) in 1997; FR1, BE2, UK55, BE1 and GR1 (upper end) in 1998; BE2, BE1, ES3, UK55 and UK92 (upper end) in 1999; UK91, BE2, BE1, DE3 and UK55 (upper end) in 2000.
IRMD: ITA and ITB (upper end) in 1995; ITA, ITB and IT8 (upper end) in 1996; ITA, ITB, IT8 and IT9 (upper end) in 1997; ITA, ITB, IT8, IT9, GR2 and GR1 (upper end) and SE08, SE0A, SE06 and SE07 (lower end) in 1998; ITA, ITB and IT8 (upper end) in 1999; ITA, ITB, IT8, IT9, GR2, GR1 and ES4 (upper end) and SE06, SE07, SE09 and SE08 (lower end) in 2000.
IA050: ITA (upper end) in 1999 and 2000 (see Appendix A1.1).

The generalised entropy index is measured where α=1 (Theil index) and α=2 (squared coefficient of variation). The Pearson correlation between the Theil index and the squared coefficient of variation has been calculated, both before and after omitting for extreme cases, which can cause misleading results. The Pearson correlation is 0.834 for 1995; 0.913 for 1996; 0.876 for 1997; 0.840 for 1998 (0.745 without the extreme cases)[50]; 0.817 for 1999 (it is 0.558 without the extreme cases); and 0.726 for 2000.[51] Thus the Theil index and the squared coefficient of variation are highly correlated.

The Atkinson index is measured where $\varepsilon = 0.25$, $\varepsilon = 0.50$ and $\varepsilon = 0.75$ in order to investigate the sensitivity to transfers at different points in the distribution of income. These indices show almost perfectly linear correlation. For 1995, for example, the Pearson correlation between the Atkinson index where $\varepsilon = 0.25$ and that index where $\varepsilon = 0.50$ is equal to 0.996, and the correlation between the Atkinson index where $\varepsilon = 0.25$ and that index where $\varepsilon = 0.75$ is 0.977; while, for 2000, the above correlations are 0.995 and 0.977, respectively. This clearly shows that as the difference between parameters increases, the Pearson correlation decreases. Additionally, the Pearson correlation, for 1995, where $\varepsilon = 0.50$ and $\varepsilon = 0.75$ is 0.990. Thus, when the parameter increases by 0.25, the correlations are higher among the Atkinson indices when they become more sensitive to transfers among top income recipients than among the Atkinson indices when they become less sensitive to transfers among lower incomes. This seems to show that income transfers among wealthy people are economically more significant than transfers among less wealthy people. Table 3.5 shows the evolution of the Pearson correlation of the Atkinson index when the difference in sensitivity parameter is constant ($\Delta\varepsilon = 0.25$). This table demonstrates that the gap between the correlation between changes at a low level of parameter (from 0.25 to 0.50) and the correlation between changes at a high level of parameter (from 0.50 to 0.75) remained almost constant.

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[50] It is due to the extreme squared coefficient of variation of Vlaams Gewest.

[51] They are significant at the 0.01 level (2-tailed) with the standard error 0.000.

Table 3.5: Pearson Correlation of the Atkinson index where $\Delta\varepsilon = 0.25$

	1995	1996	1997	1998	1999	2000
(1) IA025-IA050	0.996 (0.000)** 94	0.997 (0.000)** 94	0.996 (0.000)** 94	0.995 (0.000)** 94	0.994 (0.000)** 94	0.995 (0.000)** 94
(2) IA050-IA075	0.990 (0.000)** 94	0.992 (0.000)** 102	0.991 (0.000)** 102	0.992 (0.000)** 102	0.992 (0.000)** 102	0.992 (0.000)** 102
Difference (1-2)	0.006	0.005	0.005	0.003	0.002	0.003

Note: ** correlation is significant at the 0.01 level (2-tailed).

Table 3.6 illustrates the Pearson correlation among inequality indices for 1998. Generally, the correlations are high. However, the correlations between the squared coefficient of variation and the remaining indices have the lowest values. Excluding the squared coefficient of variation, the correlations are up to 0.934.

Table 3.6: Pearson Correlations among Income Inequality Indices for 1998

	IA025	IA050	IA075	IGE1	IGE2	IGINI	IRMD
IA025	1	0.995 (0.000)** 102	0.977 (0.000)** 102	0.994 (0.000)** 102	0.786 (0.000)** 102	0.975 (0.000)** 102	0.979 (0.000)** 102
IA050		1	0.992 (0.000)** 102	0.979 (0.000)** 102	0.736 (0.000)** 102	0.959 (0.000)** 102	0.969 (0.000)** 102
IA075			1	0.952 (0.000)** 102	0.686 (0.000)** 102	0.934 (0.000)** 102	0.941 (0.000)** 102
IGE1				1	0.840 (0.000)** 102	0.980 (0.000)** 102	0.975 (0.000)** 102
IGE2					1	0.793 (0.000)** 102	0.754 (0.000)** 102
IGINI						1	0.991 (0.000)** 102
IRMD							1

Note: ** correlation is significant at the 0.01 level (2-tailed).

Looking behind the boxplots, the descriptive statistical analysis shows that income inequality is lower in city-regions. For instance, although Spain has a high level of income inequality level, the Comunidad de Madrid has a lower level inequality than the remainder of Spain.

Due to the high correlation among income inequality indices, only the spatial dependence analysis for the Gini coefficient is explored. The univariate and bivariate Moran's I statistics computed using any spatial weights matrix are positive and statistically significant, highlighting the robustness of the results (Table 3.7). Once more, the standardised values of the statistics are approximately the same throughout the period between 1995 and 2000. This indicates a significant global tendency towards a geographical clustering of regions that are similar in terms of income inequality for the population as a whole.

Table 3.7: Moran's I for the Gini Coefficient on Income for the Whole Population (IGINI)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996	0.7179	-0.0085	0.0745	9.7503	0.8151	-0.0066	0.0751	10.9414	0.4303	-0.0103	0.0217	20.3041
	1997	0.7093	-0.0072	0.0761	9.4152	0.8067	-0.0128	0.0720	11.3819	0.4301	-0.0101	0.0221	19.9186
	1998	0.7182	-0.0133	0.0758	9.6504	0.7942	-0.0131	0.0740	10.9095	0.4186	-0.0108	0.0214	20.0654
	1999	0.6743	-0.0063	0.0734	9.2725	0.7512	-0.0091	0.0744	10.2191	0.4041	-0.0092	0.0219	18.8721
	2000	0.6733	-0.0127	0.0756	9.0741	0.7492	-0.0069	0.0741	10.2038	0.4143	-0.0087	0.0217	19.4931
Space-time correlation	1998	0.7120	-0.0062	0.0729	9.8519	0.8043	-0.0122	0.0703	11.6145	0.4273	-0.0095	0.0218	20.0367
	2000	0.6906	-0.0126	0.0715	9.8350	0.7763	-0.0094	0.0718	10.9429	0.4156	-0.0093	0.0206	20.6262
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.6332	-0.0085	0.0761	8.4323	0.7367	-0.0112	0.0807	9.2677	0.3395	-0.0104	0.0232	15.0819
	1996	0.6405	-0.0102	0.0738	8.8171	0.7556	-0.0076	0.0770	9.9117	0.3513	-0.0114	0.0229	15.8384
	1997	0.6252	-0.0118	0.0745	8.5503	0.7457	-0.0067	0.0754	9.9788	0.3425	-0.0113	0.0215	16.4558
	1998	0.6173	-0.0117	0.0760	8.2763	0.7176	-0.0135	0.0753	9.7092	0.3193	-0.0116	0.0219	15.1096
	1999	0.5761	-0.0114	0.0754	7.7918	0.6998	-0.0044	0.0765	9.2052	0.3206	-0.0102	0.0225	14.7022
	2000	0.5684	-0.0093	0.0776	7.4446	0.6959	-0.0087	0.0785	8.9758	0.3279	-0.0114	0.0222	15.2838
Space-time correlation	1998	0.6227	-0.0064	0.0759	8.2885	0.7361	-0.0098	0.0744	10.0255	0.3389	-0.0097	0.0220	15.8455
	2000	0.5849	-0.0097	0.0746	7.9705	0.6992	-0.0083	0.0749	9.4459	0.3209	-0.0093	0.0225	14.6756

Note: All statistics are significant at p=0.001, E[I]: theoretical mean, Mean: observed mean.

Local spatial autocorrelation analysis shows that there are clusters of high income inequality in southern Europe (Greece, southern Italy, Spain and Portugal), while clusters of low income inequality can be found in northern Europe (Sweden, Brandenburg and Mecklenburg) (Figure 3.19). Moreover, those clusters did not change between 1996 and 2000. For the distance band weights schemes, clusters of low income inequality expanded further to include Denmark, northern and eastern United Kingdom and the French region Est. Although Spain and Portugal represent clusters of high income inequality, the regions of Lisboa and Madrid are not in 1996 and 1998 for the rook first order contiguity, showing that income inequality is lower in city-regions.

Figure 3.19: Cluster Map for the Gini Coefficient on Income (IGINI) in 1996, 1998 and 2000

The results emphasise a certain kind of spatial heterogeneity hidden within the global spatial autocorrelation pattern. The spatial effects may perform differently between rural and urban areas and between the northern and southern European regions. First, income inequality seems to be lower in agglomerated areas, and second, the north-south divide in the European income inequality distribution may not be visible without spatial economic analysis. Homogeneity is higher within the northern and southern regions of the EU than it is between them. Considering the short evolution of income inequality within regions, it is shown that inequality has not been changed. The persistence of inequalities is clearly shown. European regions tend, over time, to maintain their relative positions in terms of income inequality, because the level of intradistributional mobility is low (Ezcurra and Pascual, 2005). Families from the very poor and very wealthy communities exhibit greater intergenerational income persistence than families living in middle-income communities (Cooper, 1998). To sum up, income inequality in each region depends not only on its own persistent characteristics, but also on those of the regions that form the neighbourhood to which it belongs and particularly within agglomerated and rural areas rather than between them, as well as within southern and northern areas rather than between them.

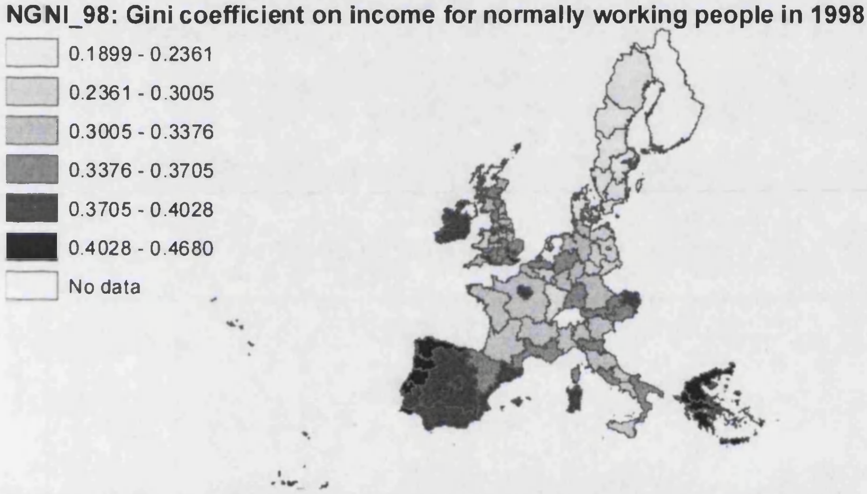
3.4.2 Within-region Income Inequality among those People Normally in Work

Income inequality among normally working people within regions is measured by the relative mean deviation index ($NRMD$), the Gini index ($NGINI$), the generalised entropy index for two different parameters ($NGE1$ when $a=1$, and $NGE2$ when $a=2$) and the Atkinson index for three parameters ($NA025$ where $\varepsilon=0.25$, $NA050$ where $\varepsilon=0.50$, and $NA075$ where $\varepsilon=0.75$), as with income inequality for the population as a whole.

Figure 3.20 shows the geographical distribution of income inequality for normally working people in 1996, 1998 and 2000.[52] As in Figure 3.17, there are differences in income inequality between different parts of Europe. Considering either the population as a whole or for normally working people, income inequality is higher in the south than in the north. Greece, the Portuguese regions of Norte, Centro and Lisboa and the Spanish regions of Noroeste and Centro have the highest levels of income inequality. A low percentage of Greek, Portuguese and Spanish workers gain employment in high added value jobs. Income inequality among normally working people is higher in the Mediterranean countries.

[52] The spatial distributions of the Theil index, the squared coefficient of variation, the relative mean deviation index and the Atkinson index are provided upon request.

Figure 3.20: Spatial Distribution of the Gini Coefficient on Income for Normally Working People (NGINI) in 1996, 1998 and 2000



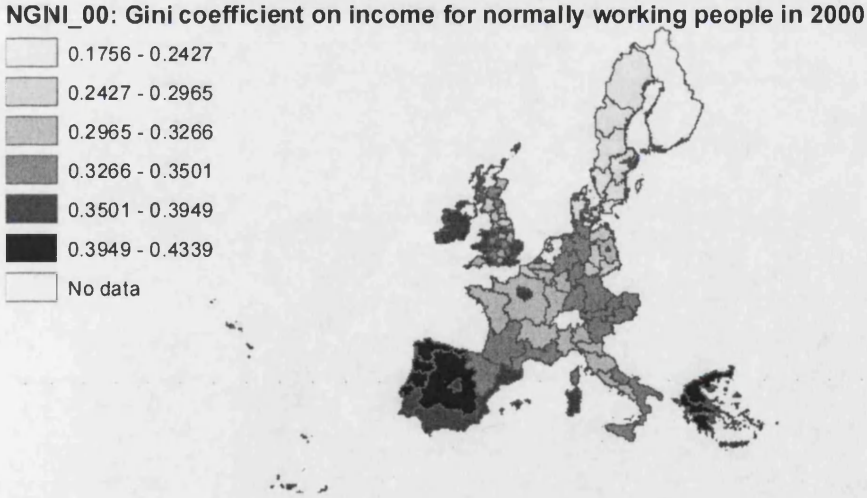
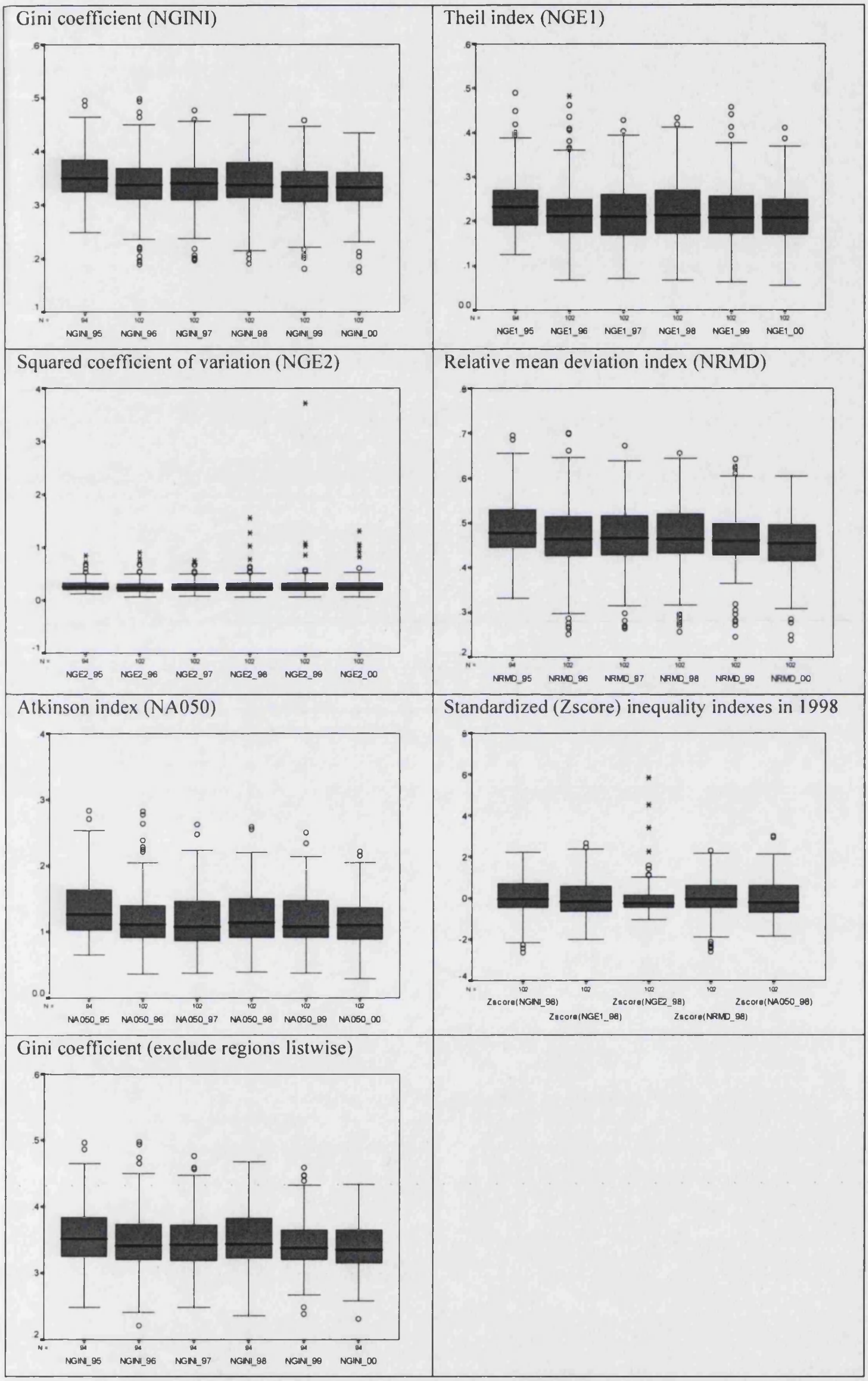


Figure 3.21 clearly displays that the boxplots for all income inequality indices for normally working people are less compact than the respective boxplots for income inequality indices for the population as a whole. There are many more outliers in Figure 3.21 than in Figure 3.18. Testing the normality assumption, the distribution of the Gini

coefficient, for example, accepts normality in 1996, 1998 and 2000, while it indicates a long right tail in 1995 and 1997 and a long left tail in 1999.[53]

[53] The ratio of skewness to standard error is 2.23 in 1995, -0.04 in 1996, 2.32 in 1997, -1.75 in 1998, -1.19 in 1999 and -2.10 in 2000.

Figure 3.21: Boxplot for Income Inequality Indices for Normally Working People



Note: extreme cases and outliers are sorted in descending order:
NGINI: ES1 and GR2 (upper end) in 1995; ES1, GR2, GR1 and PT12 (upper end), DE5, SE05, SE03, SE07, SE02, SE06 and SE08 (lower end) in 1996; GR2 and GR1 (upper end), SE03, SE07, SE06, SE02 and SE08 (lower end) in 1997; SE03, SE07, SE06 and SE08 (lower end) in 1998; GR2 (upper end), SE05, SE03, SE07, SE06 and SE08 (lower end) in 1999; and SE07, SE06, SE03 and SE08 (lower end) in 2000.

NGE1: ES1, GR2, GR1, PT12 and UK32 (upper end) in 1995; ES1, GR2, GR1, UK32, PT12, ES7, ES4 and PT15 (upper end) in 1996; GR2 and GR1 (upper end) in 1997; GR1 and UK55 (upper end) in 1998; BE2, UK92, UK55 and GR2 (upper end) in 1999; and UK91 and UK55 (upper end) in 2000.
NGE2: ES1, DE3, UK32, IE, UK84 and GR1 (upper end) in 1995; UK32, FR1, IE, ES1, GR1, GR2, UK63 and PT12 (upper end) in 1996; FR1, GR3, IE, UK55, UK63 and UK82 (upper end) in 1997; FR1, BE2, UK55, UK57, GR1, IE, AT1 and UK82 (upper end) in 1998; BE2, UK92, UK55, FR1, UK51, ES7 and UK54 (upper end) in 1999; UK91, DE3, BE2, UK55, SE01 and PT11 (upper end) in 2000.
NRMD: GR2 and ES1 (upper end) in 1995; GR2, ES1 and GR1 (upper end), SE03, SE07, SE02, SE06 and SE08 (lower end) in 1996; GR2 (upper end), SE05, SE03, SE02, SE06, SE07 and SE08 in 1997; GR2 (upper end) and DEK, SE04, SE02, SE05, SE03, SE07, SE06 and SE08 (lower end) in 1998; GR2, GR1, PT13 and ES1 (upper end), DEK, SE04, SE02, SE05, SE07, SE03, SE06 and SE08 (lower end) in 1999; and SE07, SE06, SE03 and SE08 (lower end) in 2000.
NA050: GR2 and ES1 (upper end) in 1995; GR2, GR1, ES1, PT11, ES7, GR4 and PT12 (upper end) in 1996; GR2 and GR1 (upper end) in 1997, 1998, 1999 and 2000.
Zscore in 1998: SE03, SE07, SE06 and SE08 (lower end) for NGINI; GR2 and GR1 (upper end) for NGE1; UK82, AT1, IE, GR1, UK57, UK55, BE2 and FR1 (upper end) for NGE2; GR2 (upper end), and DK, SE04, SE02, SE05, SE03, SE07, SE06 and SE08 (lower end) for NRMD; and GR1 and GR2 (upper end) for NA050.
NGINI (exclude regions listwise): ES1 and GR2 (upper end) in 1995; ES1, GR2, GR1 and PT12 (upper end), DE5, (lower end) in 1996; GR2, GR1, PT11 (upper end) in 1997; GR2, GR1, FR1 and PT13 (upper end), UKA4 and DK (lower end), in 1999; and DK (lower end) in 2000 (see Appendix A1.1).

No matter what the spatial weights matrix, Moran's I statistics show a positive spatial autocorrelation (Table 3.8). This demonstrates the robustness of the results with regard to the choice of the spatial weights matrix. A examination of the evolution of Moran's I test statistic between 1995 and 2000 shows that the standardised values of the statistic remain approximately the same over the whole period. It indicates a significant global trend towards spatial clustering of similar regions in terms of income inequality among normally working people.

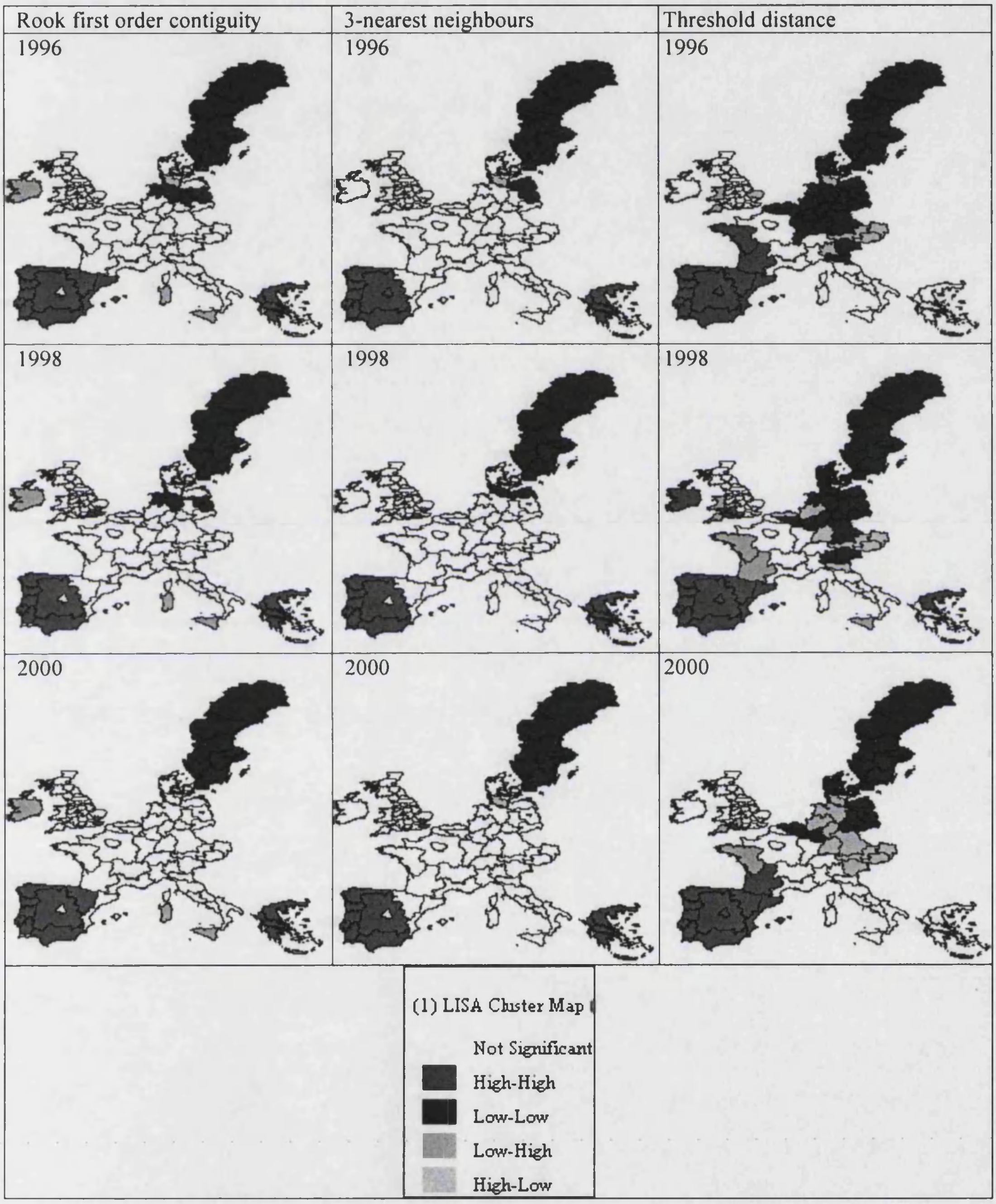
Table 3.8: Moran's I for the Gini Coefficient on Income for Normally Working People (NGINI)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996	0.7372	-0.0089	0.0740	10.0824	0.7605	-0.0091	0.0724	10.6298	0.4133	-0.0102	0.0211	20.0711
	1997	0.7494	-0.0094	0.0712	10.6573	0.7436	-0.0145	0.0746	10.1622	0.4077	-0.0096	0.0229	18.2227
	1998	0.7215	-0.0111	0.0743	9.8600	0.7219	-0.0084	0.0716	10.1997	0.3720	-0.0106	0.0220	17.3909
	1999	0.5768	-0.0092	0.0762	7.6903	0.5767	-0.0059	0.0717	8.1255	0.3232	-0.0109	0.0232	14.4009
	2000	0.6503	-0.0069	0.0725	9.0648	0.6080	-0.0121	0.0718	8.6365	0.3289	-0.0097	0.0222	15.2523
Space-time correlation	1998	0.7274	-0.0084	0.0706	10.4221	0.7387	-0.0081	0.0690	10.8232	0.3907	-0.0099	0.0214	18.7196
	2000	0.6610	-0.0087	0.0741	9.0378	0.6726	-0.0084	0.0730	9.3288	0.3567	-0.0093	0.0219	16.7123
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.5389	-0.0074	0.0755	7.2358	0.6105	-0.0089	0.0769	8.0546	0.2588	-0.0113	0.0227	11.8987
	1996	0.6028	-0.0094	0.0774	7.9096	0.6615	-0.0120	0.0746	9.0282	0.2892	-0.0103	0.0235	12.7447
	1997	0.6108	-0.0097	0.0771	8.0480	0.6540	-0.0149	0.0785	8.5210	0.2839	-0.0098	0.0227	12.9383
	1998	0.5318	-0.0080	0.0767	7.0378	0.5729	-0.0141	0.0773	7.5938	0.2025	-0.0109	0.0223	9.5695
	1999	0.3565	-0.0096	0.0787	4.6518	0.4553	-0.0067	0.0755	6.1192	0.1891	-0.0114	0.0222	9.0315
	2000	0.4703	-0.0108	0.0756	6.3638	0.5062	-0.0094	0.0773	6.6701	0.2028	-0.0115	0.0221	9.6968
Space-time correlation	1998	0.5660	-0.0085	0.0727	7.9023	0.6179	-0.0081	0.0691	9.0593	0.2443	-0.0093	0.0212	11.9623
	2000	0.4675	-0.0070	0.0724	6.5539	0.5257	-0.0063	0.0718	7.4095	0.2014	-0.0099	0.0205	10.3073

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

Figure 3.22 displays the cluster map for the Gini index on income for normally working people in 1996, 1998 and 2000. Clusters of regions with high levels of income inequality are found across Greece, Portugal and Spain, while clusters of regions with low levels of income inequality are found in northern Germany (i.e. in Brandenburg and in Schleswing-Holstein) and in Sweden. Finally, this figure is quite similar to Figure 3.19. However, the latter does not include the Italian high-high cluster.

Figure 3.22: Cluster Map for the Gini Coefficient on Income for Normally Working People (NGINI) in 1996, 1998 and 2000



Once again, the results highlight two forms of spatial heterogeneity: the EU north-south divide and the urban-rural divide. Income inequality is higher in the south and in rural areas both for the population as a whole and for those people normally in work.

Finally, the correlation between income inequality (Gini coefficient) for the population as a whole and income inequality among people normally in work is very high and statistically significant (Table 3.9).

Table 3.9: Pearson Correlation between Income inequality for the Population as a Whole (IGINI) and Income Inequality for Normally Working People (NGINI)

1995	1996	1997	1998	1999	2000
0.667 (0.000)** 94	0.711 (0.000)** 94	0.730 (0.000)** 94	0.671 (0.000)** 94	0.701 (0.000)** 94	0.688 (0.000)** 94
	0.798 (0.000)** 102	0.813 (0.000)** 102	0.786 (0.000)** 102	0.794 (0.000)** 102	0.793 (0.000)** 102

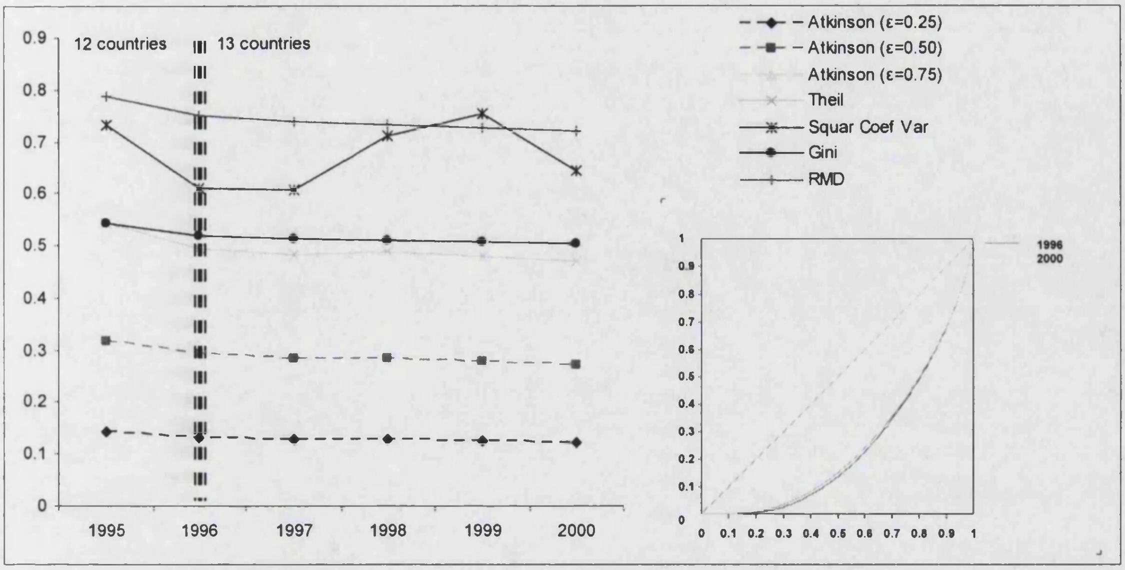
Note: ** correlation is significant at the 0.01 level (2-tailed).

3.4.3 Within-region Income Inequality for the Whole Population as a Component of European Income Inequality

In this subsection, income inequality within regions is regarded as component of the European income inequality. Hence, this subsection calculates the level of European inequality and uses the two-stage nested Theil decomposition method to explore individual level income data for the EU.

The income inequality in Europe is measured using the following indices: the relative mean deviation index, the Gini index, the generalised entropy indices and the Atkinson index. Figure 3.23 shows the short evolution of European income inequality from 1996 to 2000. More specifically, the variation in the Atkinson indices, the Theil index, the Gini coefficient and the relative mean deviation index remains the same. The fluctuation in the squared coefficient of variation indicates a different trend. There was a considerable increase between 1997 and 1999 with a peak of 0.754. After this, the coefficient fell sharply by 0.112. This figure also shows the Lorenz curves for 1996 and 2000.

Figure 3.23: The Evolution of Income Inequality in Europe



Consider the hierarchical structure of the EU: country–region–individual. Figure 3.24 shows that the between-region component is a weighted average of the within-region income inequalities. This method uses the individual as the underlying unit of analysis to measure European income inequality, rather than a spatial unit. Hence, this method applies interpersonal income inequality. The study period for the analysis runs from 1996 to 2000. Owing to the short period of time covered in the analysis, it is impossible to analyse in greater detail the changes in European income inequality over time.

Figure 3.24: Three-level Hierarchical Structure: Country–Region–Individual

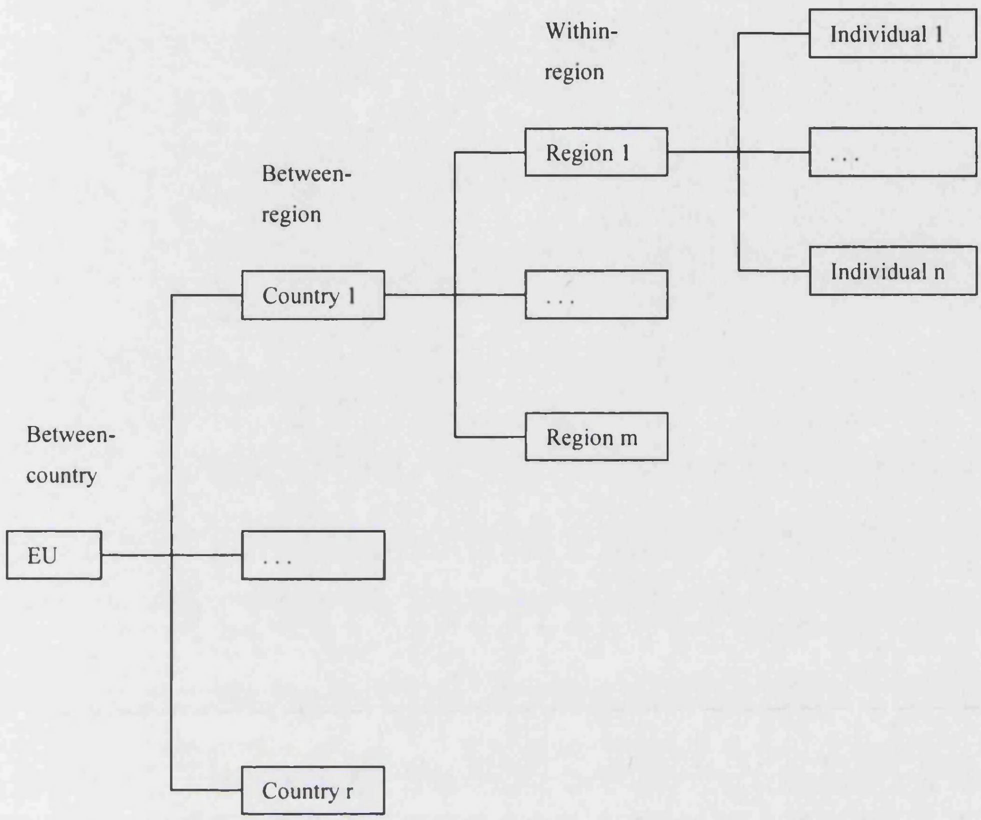
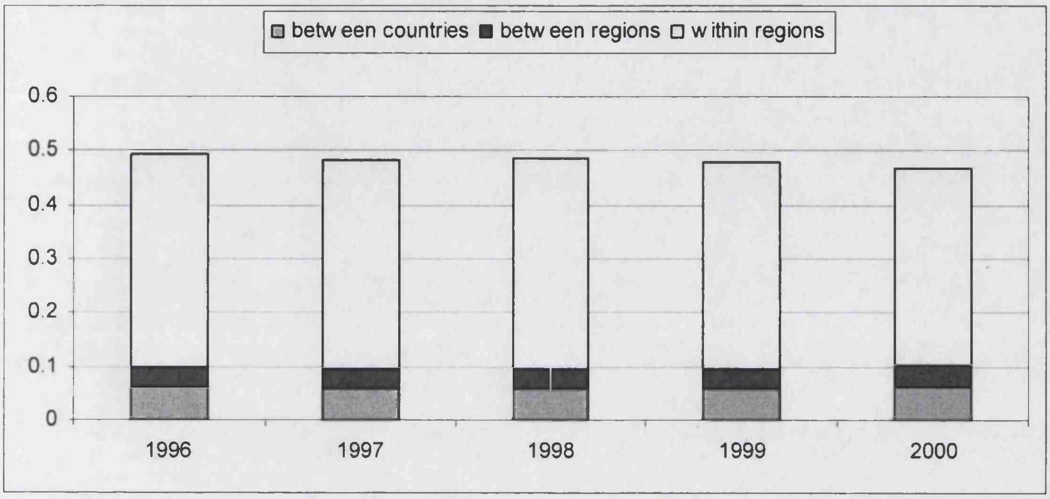


Figure 3.25 illustrates the contribution of the within-region inequalities, as well as those of between-region and the between-country inequalities to the overall level of income inequality in Europe. More explicitly, the decomposition of the overall income inequality in Europe reveals that the contribution of all components to overall inequality was quite stable between 1996 and 2000. In 1996, for example, 80.23 per cent of the overall inequality was due to the within-region component. The between-region and between-country components accounted for, respectively, 7.07 per cent and 12.70 per cent. In 2000, the overall income inequality was 77.97 per cent, 8.97 per cent and 13.06 per cent due to the within-region, between-region and between-country components, respectively. Hence, the within-region component accounts for a large proportion of all European income inequality. Additionally, the analysis indicates that the between-country component was much more significant than the between-region component, accounting for about 19.77 per cent in 1996 and 22.03 per cent of overall inequality. Both between-region and between-country inequality of the EU remained stable at a very low level, indicating that interregional and international migration is very low. In general, inequalities based on an average level of income distribution (i.e. national income distribution) are much lower than inequalities based on total net personal

income, indicating that relatively high inequalities exist among individuals within each region.

Figure 3.25: Three-level Income Decomposition by Theil Index for the EU from 1996 to 2000



To sum up, the within-region inequalities are much more prominent than the between-region and between-country inequalities. This observation suggests that policy-makers should pay more attention to within-region inequalities rather than between-region and between-country inequalities in order to formulate better welfare policies.

3.5 Correlation between Income Per Capita and Income Inequality

The linear correlation between income per capita and income inequality for the population as a whole and for normally working people is measured using the Pearson coefficient. Table 3.10 shows that the correlation between income per capita and income inequality is negative and statistically significant. The higher the regional per capita income, the lower the inequality level within that region, and vice versa. This negative correlation is higher when income inequality is measured using the Atkinson index and is lower when it is measured using the squared coefficient of variation. Apart from the correlation between income per capita and the squared coefficient of variation, the negative relationship between income per capita and any other inequality index has not changed between 1996 and 2000. Finally, the Pearson correlations for the population as a whole are higher than the respective Pearson correlations for normally working people.

Table 3.10: Pearson Correlation between Income per Capita and Income Inequality

PEARSON CORRELATION: Income per capita for the whole of the population (IMN) and income inequality for the whole of the population						
	1995	1996	1997	1998	1999	2000
IA025	-0.600 (0.000)** 94	-0.654 (0.000)** 94 -0.685 (0.000)** 102	-0.758 (0.000)** 94 -0.753 (0.000)** 102	-0.698 (0.000)** 94 -0.685 (0.000)** 102	-0.687 (0.000)** 94 -0.666 (0.000)** 102	-0.733 (0.000)** 94 -0.710 (0.000)** 102
IA050	-0.592 (0.000)** 94	-0.644 (0.000)** 94 -0.677 (0.000)** 102	-0.768 (0.000)** 94 -0.765 (0.000)** 102	-0.721 (0.000)** 94 -0.710 (0.000)** 102	-0.718 (0.000)** 94 -0.699 (0.000)** 102	-0.765 (0.000)** 94 -0.744 (0.000)** 102
IA075	-0.559 (0.000)** 94	-0.613 (0.000)** 94 -0.650 (0.000)** 102	-0.772 (0.000)** 94 -0.769 (0.000)** 102	-0.732 (0.000)** 94 -0.721 (0.000)** 102	-0.736 (0.000)** 94 -0.718 (0.000)** 102	-0.793 (0.000)** 94 -0.773 (0.000)** 102
IGE1	-0.595 (0.000)** 94	-0.655 (0.000)** 94 -0.686 (0.000)** 102	-0.742 (0.000)** 94 -0.736 (0.000)** 102	-0.658 (0.000)** 94 -0.647 (0.000)** 102	-0.634 (0.000)** 94 -0.614 (0.000)** 102	-0.690 (0.000)** 94 -0.665 (0.000)** 102
IGE2	-0.374 (0.000)** 94	-0.535 (0.000)** 94 -0.578 (0.000)** 102	-0.512 (0.000)** 94 -0.529 (0.000)** 102	-0.194 (0.061) 94 -0.221 (0.025)* 102	-0.063 (0.547) 94 -0.081 (0.417) 102	-0.265 (0.010)** 94 -0.259 (0.009)** 102
IGINI	-0.609 (0.000)** 94	-0.654 (0.000)** 94 -0.679 (0.000)** 102	-0.730 (0.000)** 94 -0.703 (0.000)** 102	-0.676 (0.000)** 94 -0.635 (0.000)** 102	-0.661 (0.000)** 94 -0.615 (0.000)** 102	-0.686 (0.000)** 94 -0.637 (0.000)** 102
IRMD	-0.639 (0.000)** 94	-0.681 (0.000)** 94 -0.705 (0.000)** 102	-0.740 (0.000)** 94 -0.718 (0.000)** 102	-0.703 (0.000)** 94 -0.669 (0.000)** 102	-0.690 (0.000)** 94 -0.650 (0.000)** 102	-0.700 (0.000)** 94 -0.659 (0.000)** 102

PEARSON CORRELATION: Income per capita for normally working people (NMN) and income inequality for normally working people						
	1995	1996	1997	1998	1999	2000
NA025	-0.567 (0.000)** 94	-0.571 (0.000)** 94 -0.574 (0.000)** 102	-0.640 (0.000)** 94 -0.593 (0.000)** 102	-0.481 (0.000)** 94 -0.441 (0.000)** 102	-0.443 (0.000)** 94 -0.397 (0.000)** 102	-0.470 (0.000)** 94 -0.422 (0.000)** 102
NA050	-0.634 (0.000)** 94	-0.627 (0.000)** 94 -0.627 (0.000)** 102	-0.715 (0.000)** 94 -0.669 (0.000)** 102	-0.613 (0.000)** 94 -0.563 (0.000)** 102	-0.593 (0.000)** 94 -0.537 (0.000)** 102	-0.606 (0.000)** 94 -0.549 (0.000)** 102
NA075	-0.685 (0.000)** 94	-0.669 (0.000)** 94 -0.671 (0.000)** 102	-0.777 (0.000)** 94 -0.743 (0.000)** 102	-0.726 (0.000)** 94 -0.683 (0.000)** 102	-0.721 (0.000)** 94 -0.674 (0.000)** 102	-0.723 (0.000)** 94 -0.673 (0.000)** 102
NGE1	-0.491 (0.000)**	-0.503 (0.000)**	-0.558 (0.000)**	-0.337 (0.001)**	-0.283 (0.006)**	-0.331 (0.001)**

	94	94 -0.514 (0.000)** 102	94 -0.516 (0.000)** 102	94 -0.318 (0.001)** 102	94 -0.256 (0.000)** 102	94 -0.297 (0.002** 102
NGE2	-0.169 (0.103) 94	-0.182 (0.079) 94 -0.223 (0.024)* 102	-0.214 (0.038)* 94 -0.216 (0.029)* 102	0.138 (0.183) 94 0.123 (0.218) 102	0.143 (0.170) 94 0.142 (0.155) 102	0.036 (0.734) 94 0.056 (0.575) 102
NGINI	-0.502 (0.000)** 94	-0.522 (0.000)** 94 -0.509 (0.000)** 102	-0.514 (0.000)** 94 -0.443 (0.000)** 102	-0.387 (0.000)** 94 -0.328 (0.001)** 102	-0.365 (0.000)** 94 -0.302 (0.002)** 102	-0.345 (0.001)** 94 -0.292 (0.003)** 102
NRMD	-0.503 (0.000)** 94	-0.517 (0.000)** 94 -0.504 (0.000)** 102	-0.457 (0.000)** 94 -0.397 (0.000)** 102	-0.356 (0.000)** 94 -0.303 (0.002)** 102	-0.331 (0.001)** 94 -0.275 (0.005)** 102	-0.286 (0.005)** 94 -0.246 (0.013)* 102

Note: ** correlation is significant at the 0.01 level (2-tailed); * correlation is significant at the 0.05 level (2-tailed).

3.6 Conclusions

This chapter has illustrated the following underpinning outcomes. The spatial distribution of income per capita and income inequality is not uniform, but rather it is characterised by asymmetries. The application of global and local spatial association tests facilitates the detection of income patterns across European regions. The spatial interaction patterns and structures are represented by the spatial weights matrices. Global and local statistics lead to the same results for spatial autocorrelation and space-time correlation, highlighting the robustness of the results with regard to the choice of the spatial weights matrix. Global tests show that pecuniary and technological externalities spill over the barriers of regional economies. The diffusion of technology is likely to be higher among regions that are geographically close to one another as compared to economies that are geographically more distant (Vaya et al. 2004). The income inequality (resp. income per capita) in any given region seems to depend on the initial income inequality (resp. initial income per capita) in that region, as well as on a weighted average of initial income inequality (resp. initial income per capita) in neighbouring regions. Local tests show that income disparities are determined by region-specific characteristics such as location. There are striking disparities in income per capita and inequalities between different parts of Europe, particularly between the northern and the southern regions of Europe, while GDP per capita seems to be more randomly distributed over space. There are clusters of high income inequality and low income per capita in southern Europe (Greece, southern Italy and Spain), while there are clusters of low income inequality and high income per capita in northern Europe (Germany, Belgium, Sweden and Denmark). The economic surroundings of a region seem to have a bearing on its economic development perspectives. For instance, a poor southern region surrounded by other poor regions will stay in that state of economic development, whereas a poor northern region surrounded by richer regions has a greater probability of achieving a more advanced state of economic development. Hence, the prevalence of interregional externalities can create poverty traps. The clusters of the poorest European regions in southern Europe may create a great disadvantage for those regions. Furthermore, the results reveal a second spatial regime: the urban-rural polarisation. Hence spatial dependence performs differently according to level of urbanisation. The higher the degree of urbanisation of a region (i.e. city-regions), the lower the income inequality within the region, and the higher the income per capita. The diffusion of technology generated by the southern city-regions is likely to alleviate the poverty trap that has been created by the EU north-south pattern. A city-region with high income per capita and low income inequality is likely to enhance the economic perspectives of the neighbouring poor regions. Nevertheless, the EU north-south pattern seems to be stronger than EU urban-rural pattern. For instance, in most cluster maps the Comunidad de Madrid region (city-region) performs as spatial outlier, because it is surrounded by regions with low income per capita and high income inequality levels. Finally, the within-region component of income inequality constitutes the major portion of the European inequality, while the between-region component is small in comparison.

4 Chapter Four. An Analysis of European Educational Distribution: Educational Attainment and Inequality

4.1 Introduction

This chapter concerns the exploration and analysis of educational distribution in terms of educational attainment and inequality. Spatial effects are also taken into consideration. The chapter sets out to investigate more closely the space-time dynamics behind the distributions of the average education level and inequality in education within regions in order to show that spatial autocorrelation and spatial heterogeneity are, indeed, required features in an analysis of distribution in European education. Human capital is expected to be geographically autocorrelated due to certain processes that connect different regions, such as educational externalities and national institutional differences. Knowledge diffusion may be particularly important in measuring regional disparities, because it directly affects regional interactions which are summarised in spatial weights matrices. This chapter examines the way that human capital is spatially distributed in the EU and the way in which spatial patterns have probably changed over the period of study (1995-2000). It emphasises the magnitude of geographical spillover effects in labour market and highlights the underlying human capital diffusion process.

This chapter is organised in three subsequent sections. In Section 4.2, definitions and measurements of educational attainment are presented. Two proxies of educational stock are used: the average education level completed and the average age at which the highest education level was completed. Section 4.3, in turn, is concerned with the definitions and measurements of educational inequality, which is conceptualised as average disproportionality. Next, the within-region educational inequality as a component of the educational inequality in Europe is analysed following the two-level Theil decomposition method proposed by Akita (2003). Section 4.4 looks at the relationship between the average educational attainment and inequality in educational distributions.

4.2 Defining and Measuring Educational Attainment

A first issue is how to define, measure and compare skills, knowledge and competences over time and across regions. This section explores the formal definition and measurement of two proxies for educational attainment. More specifically, the first subsection focuses on the recent definitions of human capital stock and considers a more formal approach to measure that stock, highlighting its pros and cons. The second subsection looks at the first proxy for educational attainment, which is defined as the average education level completed, while the third analyses the average age at which the highest education level was completed, which is the second proxy for educational attainment. Both subsections place an emphasis on spatial effects. The fourth subsection reveals the relationship between these proxies.

4.2.1 Formal Definition of Educational Attainment

As mentioned earlier in this study, educational attainment can be defined in terms of various human attributes, such as the knowledge, skills and competences embodied in individuals that are relevant to economic activity (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998). Broadly speaking, measurements of educational attainment could be classified into two basic categories.

The first category describes the educational attainment of the population within a society in terms of the percentage who have successfully completed various levels of formal education as defined by the International Standard Classification of Education (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998). The term 'level' is defined in relation to the years of study and the age associated with an educational cycle. These indicators show how many people have completed each level of initial education. A related measure is the average number of years of schooling completed. It assumes that a year of education will add a constant quantity to the human capital stock, whether undertaken by a primary school child or a post-graduate student. Recent studies measuring human capital stock in terms of the percentage who have gained upper-secondary and tertiary level qualifications or the estimated average number of years spent in completed episodes of primary, secondary and tertiary education include the work of Ram (1990), Barro (1991), Benhabib and Spiegel (1994), Gemmell (1996), Pritchett (1996), Temple (1999) and Ciccone (2004), among others.

The second category offers a relatively novel approach to the measurement of skills and competences consistent with International Adult Literacy Survey. In this assessment of human capital stock, adults are tested on three literacy scales (prose, document and quantitative) and assigned to one of five levels of literacy on each scale. The levels represent the varying degrees of complexity in the components of literacy skills needed in different situations. The literacy scores reflect the degree to which adults develop or lose skills initially acquired at school. Fewer studies have placed an emphasis on the measurement of the quality of educational attainment (i.e. scores in internationally comparable examinations, talent in engineering, percentage performing at each of five levels of measured literacy in three domains), those which have include the works of Murphy et al. (1991), Tallman and Wang (1994), Hanushek and Kimko (2000) and Barro (2001).

This analysis focuses on the educational attainment of individuals as a measurement of human capital stock, rather than the more complex relationships which combine both the quantity and the quality of human capital endowments within regions. Besides, the measurement of human capital stock has been strongly guided by what it is possible to measure, rather than by what it is desirable to measure (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998: 89). In this study, two proxies for educational achievement are presented, which are aggregate indicators of formal education based on the ECHP survey. This, however, implies 'aggregation biases' of various sorts and the imposition of restrictions, such as homogeneity within regions (Sianesi and Van Reenen, 2003). Consequently, some variations in human capital are likely to be lost. Inferences at the individual level are made using aggregate data for a region.

The first proxy for educational attainment is the average (of the highest) education level completed. It considers three grades: less than the second stage of the secondary education level, the second stage of the secondary education level, and a recognised third education level. Individuals are classified into any one of the three educational categories, which are mutually exclusive. This proxy is collected via the regionalised microeconomic variable '*Highest level of general or higher education completed*', which is extracted from the ECHP dataset. The three levels of the formal education are defined by the International Standard Classification of Education and permit international comparisons. This proxy is based upon two crucial assumptions. The first assumption is that an increment in education level completed, undertaken either by a primary or by a secondary student, adds a constant quantity to human capital stock. The second assumption is that acquisition of postgraduate degrees will not add any quantity to human capital stock, because both graduate and postgraduate degrees belong to the same category ('recognised third level education'). This proxy has been defined by Psacharopoulos and Arriagada (1986) and Ram (1990). The average education level completed is given by the following index:

$$EMN = \sum_j L_j S_j ,$$

where $j \in \{1,2,3\}$ are the educational categories, L_j is the proportion of the respondents who fall in the j^{th} category and S_j, at the risk of some oversimplification, denotes an assessment of each category. More specifically, $S_1 = 2$ 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.[54]

This proxy, in practice, cannot be compared across European countries with different requirements for completing any given formal educational level. When comparing educational attainment across countries, there is no consistent definition of what a particular level means in terms of knowledge, competences and skills (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998). The completion of a given level may be associated with somewhat different lengths of study in different regions.[55] The duration of some upper secondary and tertiary programmes differ. For instance, there are many short programmes at upper secondary level in France (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998). The education systems and structures of each country vary in terms of resources, duration and the preparation of entering students (Sianesi and Van Reenen, 2003). For example, the requirements in terms of the knowledge and skills that must be met in order to pass courses or be awarded particular grades vary widely among countries. Thus, national data on educational attainment are hardly comparable, due to the significant differences in education systems, structures and traditions (Rodríguez-Pose and Vilalta-Bufi, 2005).

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[54] Although the availability of educational categories is very limited (three categories only) and the concept of 'education level' is broad due to differences in national education systems, this assessment is likely to correspond to the numbers of years of schooling, because if the first stage of secondary education level is a base year, the number of years of the second stage of secondary education level is, for most European countries, half the number of years required for a recognised third education level. In other words, the minimum duration required to complete the second stage degree of secondary education is three years, the same number of years required for a first university degree (Bachelor degree).

[55] However, the Bologna protocol will reduce the problem of comparability in the future.

This proxy measures the amount of education undertaken and certifies, within the different context of each European country's education system, acquisition of certain types of knowledge and skill. However, this proxy ignores learning on courses that do not lead to a recognised qualification, such as enterprise-based or on-the-job training programmes. Finally, the completion of a level of education certifies certain knowledge and skills without taking into account the time required for completion.

The second proxy for educational attainment is the average age of individuals at which the highest grade was completed. It is collected by the microeconomic variable '*Age at which the highest level of general or higher education was completed*', which also is extracted from the ECHP dataset. This proxy assumes that a year of education will add a constant quantity to human capital stock, whether undertaken by a secondary or tertiary school student. Hence a year of education is a constant unit, regardless of level. Furthermore, when assessing the impact of an additional year of education, it is assumed that one year of, for instance, secondary schooling is equivalent to a year at the same grade in other regions and countries. The second proxy is defined as

$$AMN = \frac{1}{N}\sum_{i}^{N} AGE_i ,$$

where $i \in \{1,2,...,N\}$ are individuals and AGE_i is the age of the i^{th} individual when the highest education level was completed. This proxy is likely to correspond to differences in duration of studies, but only when there is not any formal period of educational inactivity, such as study leave or a gap year. One potential drawback is that this method may add periods of short term unemployment and economic inactivity to human capital endowments. This proxy is likely to add training periods to human capital stock, but only when these have been completed before the highest education level was reached. Hence, it is likely to consider a 'wider' definition of human capital investment, encompassing experience, learning-by-doing and on-the-job training. Through the measurement of human capital stock in terms of average age it is possible to develop indirect measures of the value placed on skills in the workplace and of the benefits to individuals of work-related training. The main point is that the use of age at highest qualification to measure human capital includes any activity prior to final qualification, some of which may be spent building human capital and some not.

The ideal measures of human capital would be in terms of the output of education, but due to the difficulties of obtaining such measures, input measures tend to be used instead (Sianesi and Van Reenen, 2003: 168). The proxies for educational stock outlined here are measured in terms of the input of formal education without considering the output of knowledge, skills and competences embodied in individuals, and, for the most part, without taking on board a wider definition of human capital investment encompassing experience and learning-by-doing (Sianesi and Van Reenen, 2003). Completion of educational levels is only broadly associated with certain forms of economically-relevant knowledge, skills and competence and does not look at the human capital stock attributed directly. A certificate of tertiary education, for example, registers the fact that a student has passed certain courses and exams, but does not certify that he or she has spent a certain amount of time studying (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998: 82). Hence, such measures of regional differences in educational attainment cannot explain differences in adult literacy performance. In other words, they do not measure how much in practice such attributes are worth in economic terms.

Neither proxy takes into account the fact that skills are lost through disuse. They ignore the depreciation of human capital. The depreciation of skills is often associated with unemployment and economic inactivity. A person's qualifications are kept for life, while the qualities required to gain them may depreciate over time (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development, 1998: 82). The study carried out by the Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development (1998) shows that, firstly, in some countries many less-educated people have a high level literacy, while in others many better-educated ones have a low level of literacy; and secondly, the same level of education yields, on average, very different literacy outcomes. According to that study, direct skill measures provide a more accurate measure of human capital stock, because they better reflect learning, training and skill attrition throughout life. Nevertheless, measuring adult skills directly gives only a partial picture of the attributes relevant to economic activity, whereas it does not take into account the depreciation of skills during adulthood.

To sum up, the proxies analysed are more measurements of the quantity and availability of a region's human resources (input measures), rather than measurements of the quality of human capital endowments (output measures). In this study, the quality of education is not taken into consideration. However, in measuring the quantity of education, one only gains a crude idea of skill differences (Hanushek and Kimko, 2000).

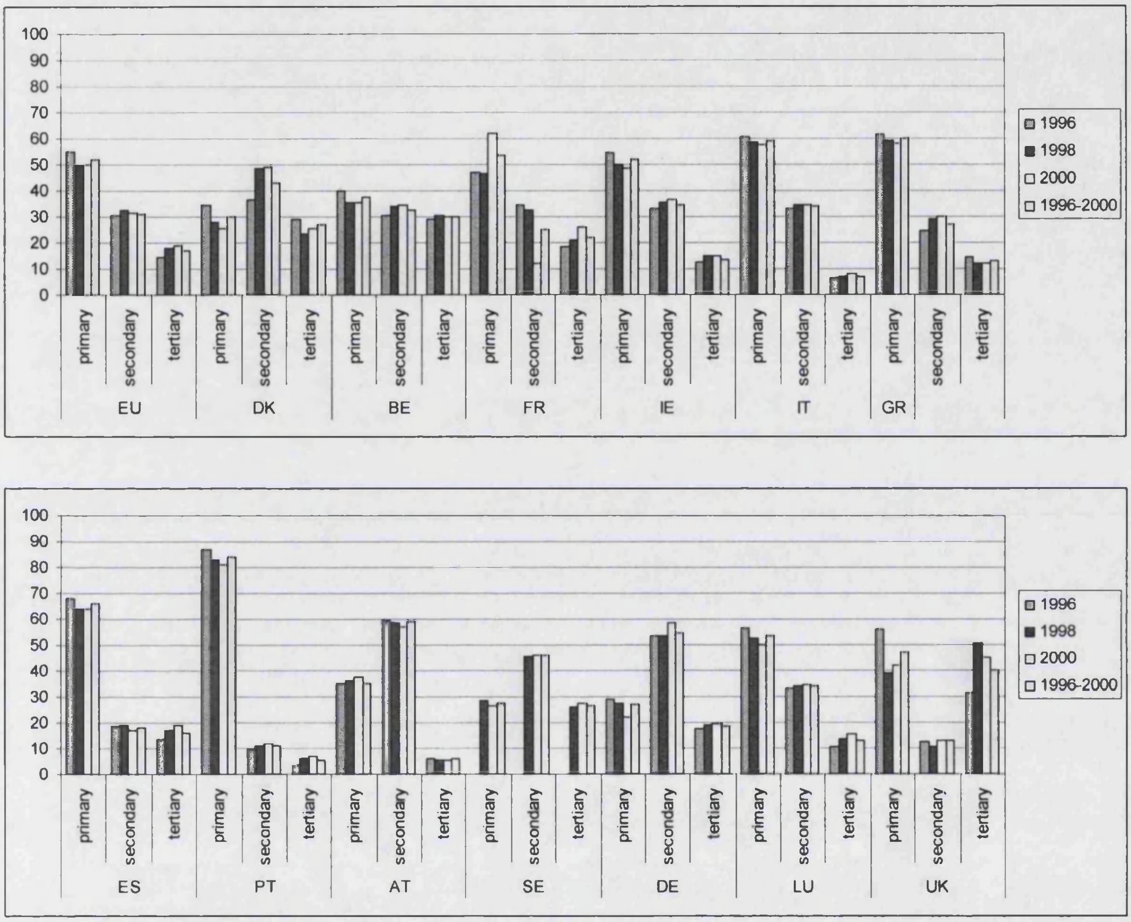
4.2.2 *Average Education Level Completed*

This subsection considers educational attainment in terms of the average education level completed. It regards human capital stock as a quantitative variable and investigates ESDA on human capital endowment within European regions. However, a preliminary analysis of national educational attainment is obtained, exploring human capital as a qualitative variable.

According to the International Standard Classification of Education, the educational attainment of the respondents within Europe is explored in terms of the *percentage* of people who have only completed the primary (or the first stage of secondary education), and those who have completed the secondary or the tertiary education level. Between 1995 and 2000, 48 per cent of European respondents who had completed formal education were found to hold a secondary education level diploma and 17 per cent of them had also completed tertiary education. Figure 4.1 displays the recent evolution of educational attainment by country, along with the formal education level completed. The results show that the Portuguese and then Spanish citizens are the least educated in Europe, whereas Denmark, Sweden and Belgium have the highest and also the most equally distributed human capital endowments. Danish, Swedish and Belgian citizens may have, for example, a higher level of aspiration and have put more effort into their career (Hansen, 2001). They may have maximised their economic welfare by investing a larger amount in human capital (Becker and Chiswick, 1966). Hansen (2001), however, notes that the fact that a higher level of education has been attained by a large proportion of the Swedish and British population is likely to lead to inflation in the value of educational credentials. According to Figure 4.1, Italy, Portugal and Austria have the smallest percentage of highly-educated people. Ireland and Luxembourg's segmented distribution of educational achievement follows the European distribution. The percentage (47 per cent) of British who have completed only primary education is high and is close to the percentage (42 per cent) of them who hold a certificate of higher education (tertiary). This demonstrates a polarisation of educational attainment, which means an increase in the homogeneity within groups of education levels, but also an increase in the distance between groups. The distance between the primary and the tertiary education level completed is likely to represent the gap between an individual's lifetime of effort in their career or a lifetime of economic opportunities. Between 1995 and 2000, the component of human capital stock at different education levels remained almost the same for secondary education and increased slightly for higher education

(14.6 per cent in 1996, 17.9 per cent in 1998 and 19.8 per cent in 2000). Nevertheless, the cross-country differences in terms of the percentage at each education level completed are significant.

Figure 4.1: Percentage of Respondents with Primary, Secondary or Tertiary Education Level Completed by European Country in 1996, 1998 and 2000



Assessing each educational level (as described above, by awarding a score of 0 for first stage of secondary education level completed; 1 for second stage of secondary education level completed; and 2 for recognised third education level completed), human capital stock is transformed into a quantitative variable. On calculating the average education level completed of all European citizens, it was found that educational attainment in Europe has increased somewhat. For instance, it increased from 0.5 in 1996 to 0.7 in 2000.

Mapping the average education level completed enables one to establish whether educational attainment within regions is randomly distributed over the EU or whether there are similarities between regions. Figure 4.2 shows the spatial distribution of the average education level completed within regions in 1996, 1998 and 2000. There are striking disparities in human capital endowments between different regions of Europe. In Portugal, Spain, Italy and Greece, the average education level completed is lower than anywhere else in the Union. Educational attainment is approximately half of the EU average in those countries. It is well above average in northern Europe, including the United Kingdom, Denmark, Sweden, Belgium and Germany. Northern regions with relatively high human capital endowment are and remain localised close to other regions with relatively high human capital endowments, while southern regions with relatively low human capital endowments are and remain localised close to other regions with relatively low human capital endowments.

The disparities in educational attainment appear to be higher at a national level than at a subnational one, because the guidelines for education systems and structures are, as a general rule, set nationally (Rodríguez-Pose and Vilalta-Bufi, 2005: 552). European regions have to comply with national guidelines and curricula (Rodríguez-Pose and Vilalta-Bufi, 2005: 552). Most institutions, even private or religious schools, are under the control of national governments and usually funded by government expenditures. For instance, university fees are generally set nationally. Nevertheless, within the United Kingdom and Germany there are striking regional disparities, demonstrating human capital segregation. More specifically, in the United Kingdom educational attainment measured as the average education level completed is highly concentrated in southern (Bedfordshire, Hertfordshire, Berkshire, Buckinghamshire, Oxfordshire, Essex, Hampshire, Isle of Wight and Kent) and northern (Scottish) regions; and in Germany, human capital endowment is higher in the north-eastern regions of the former East Germany (Brandenburg, Mecklenburg-Vorpommern, Berlin, Sachsen, Sachsen-Anhalt and Thüringen). German regions are likely to have some form of power over a devolved education system, as is illustrated by the subnational disparities in educational attainment. Moreover, the German public schools are subject to state, and not federal, laws, which is why there are considerable differences between states.[56] The regional disparities in Britain and Germany may be linked to the spatial level of analysis, since the aggregation level in the United Kingdom and Germany is NUTS II. However, data that are close together in space (i.e. NUTS II) are more often alike than those that are relatively far apart (i.e. NUTS I) (Cressie, 1993). The regions in NUTS I level may be too large and the unobserved heterogeneity may create an ecological fallacy. The British

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and German disparities are also probably from the result of boundary mismatching between NUTS II and the actual market boundaries over which economic processes operate.

Considering the urbanisation level, human capital endowment is higher in city-regions (Greater London, Île de France, Région de Bruxelles) than elsewhere. These cities are likely to attract highly-qualified migrants in search of better working prospects. Many people move to core cities in search of better educational opportunities, employment, further career prospects and higher standards of living. The higher education institutions are generally located in cities. The local provision of higher education institutions may itself contribute to a growth in the local stock of human capital (Bennett et al., 1995). Educational stock has important effects on the structure of the local economy, either city or region. However, the existence of highly-qualified institutions in a region or city is not sufficient to ensure a high human capital endowment. The ability of the higher education infrastructure to increase the stock of human capital within a regional market depends on the ability of the region to attract, as well as to retain, high quality students and workers (McCann and Sheppard, 2001). The institutions in the major European cities seem to attract students of sufficient learning ability and the urban labour market may retain them once they have graduated. This outcome depends on the previous migration history of the individual (Davanzo, 1976) and on their personal unemployment (Davanzo, 1978) (McCann and Sheppard, 2001: 137). Highly-educated workers are more likely to make the necessary moves required in order to achieve higher promotion. Furthermore, they are prone to migrate more as a way to achieve greater employment returns. These findings are consistent with those of Fingleton (2003), who noted that, although there are undoubtedly variations due to differences in national education systems, structures and traditions, it is revealing that regions with high levels of educational attainment are those urbanised, non-peripheral regions which one would consider to be the productive core of Europe (Fingleton, 2003: 12). He also observed that '*regions specialised in high value added manufacturing, research and development and service activities will also have work-forces with commensurate skills*' (Fingleton, 2003: 13).

Figure 4.2: Spatial Distribution of Average Education Level Completed (EMN) in 1996, 1998 and 2000

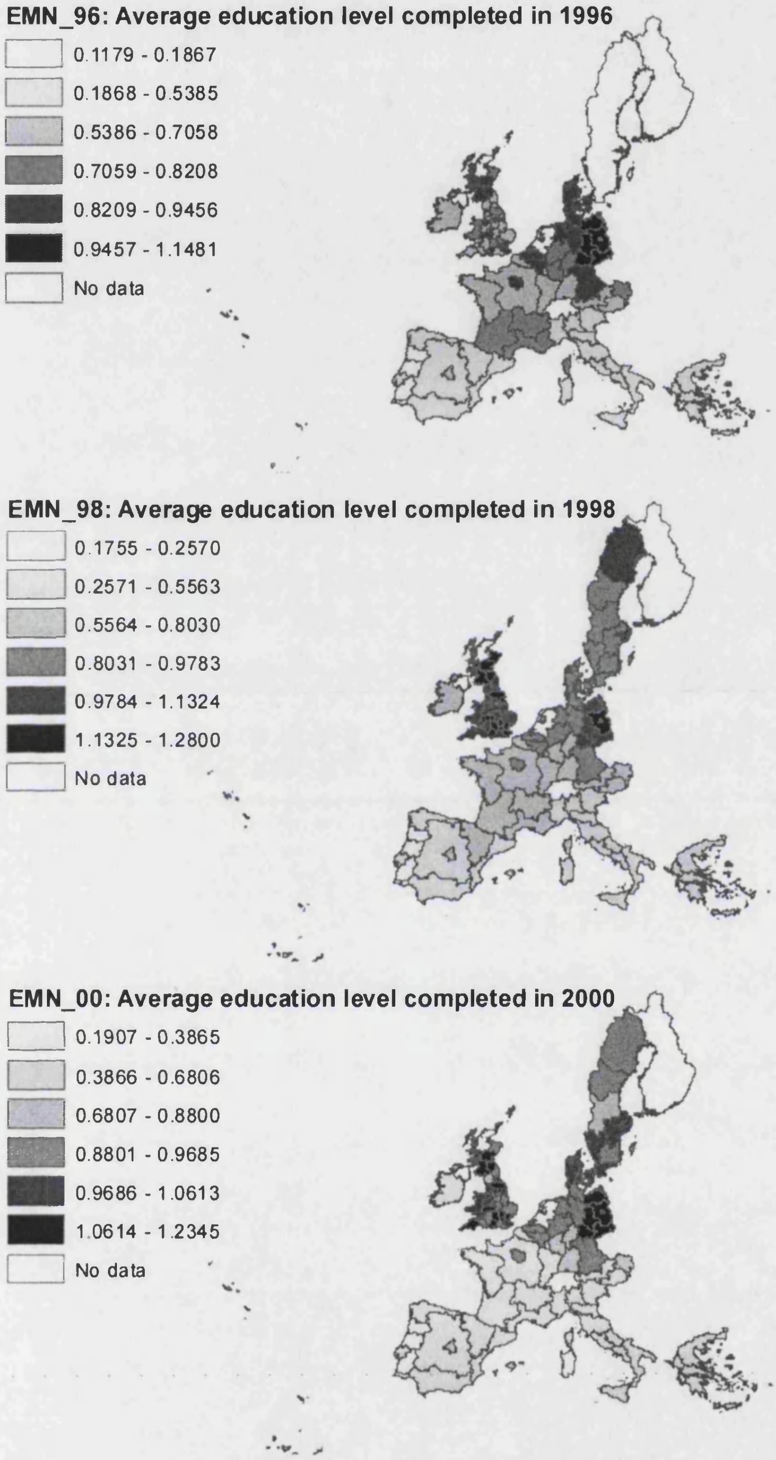
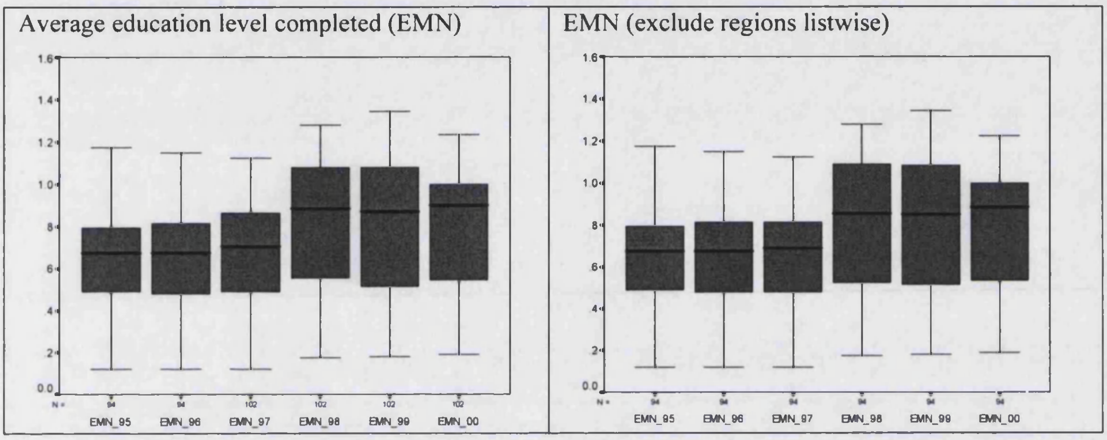


Figure 4.3 displays the univariate boxplot for the average education level completed within European regions from 1995 to 2000. Although the segments of education are unequally distributed over space, there are no outliers. This is a sign of the compactness of the European distribution of educational attainment. The median remained constant between 1995 and 1997, and between 1998 and 2000 (0.89 in 1998, 0.87 in 1999 and

0.90 in 2000), but increased significantly (by 0.19) from 0.70 in 1997 to 0.89 in 1998. The average had the same evolution. Furthermore, the interquartile range increased from 1997 to 1998, indicating increased variability in the average education level completed. The interquartile range and the variations in the whiskers are somewhat longer for 1999, inducating that human capital endowments cover a larger spectrum. Finally, the distribution of the average education level completed in Europe accepts normality over the period 1995–1999, but rejects it in 2000. The ratio of skewness to standard error is negative which indicates a left tail.[57]

Figure 4.3: Boxplot for Average Education Level Completed (EMN)



Short trends in the evolution of human capital disparities across the EU can be captured not only by distribution maps and boxplots, but also by simple statistical measures of spatial dependence, such as Moran's I test statistic. Constructing the rook first order contiguity spatial weights matrix for average education level completed, Moran's I global spatial autocorrelation statistics are high (Table 4.1). These statistics show that there is a high positive spatial autocorrelation of human capital endowment. Considering the space-time correlation, it is shown that the Moran's I statistic between a region's human capital endowment in 1998 and neighbouring regions' endowment in 1996 (which is the space-time correlation of human capital stock in 1996) is 0.5547, when Sweden is excluded, and the space-time correlation in 1996 is 0.6896. Both space-time correlation statistics show a positive spatial correlation. Moran's I statistics computed using the 3-nearest neighbours spatial weights matrix are also high. Finally, the threshold distance schemes also show a positive spatial autocorrelation, but it is

[57] The ratio of skewness to standard error is -0.63 in 1995, -0.91 in 1996, -1.69 in 1997, -1.78 in 1998, -1.20 in 1999 and -2.13 in 2000.

lower than those registered using the other schemes. For instance, the spatial autocorrelation in 1999 is just 0.3802, when all countries are included. However, the standardised values of the Moran's I statistic appear to be very high, possibly indicating, once again, a spatial scale problem (Ertur and Le Gallo, 2003: 64). The evolution of Moran's I test statistic over the period 1995–2000 shows that the standardised values of the statistic remain approximately the same over the whole period. This indicates a significant global tendency towards geographical clustering of similar regions in terms of average education level completed. The application of Moran's I statistics lead to the same results for the sign (positive) and significance of global spatial dependence, highlighting the robustness of the results, with regard to the choice of the spatial weights matrix.

Table 4.1: Moran's I for Average Education Level Completed (EMN)

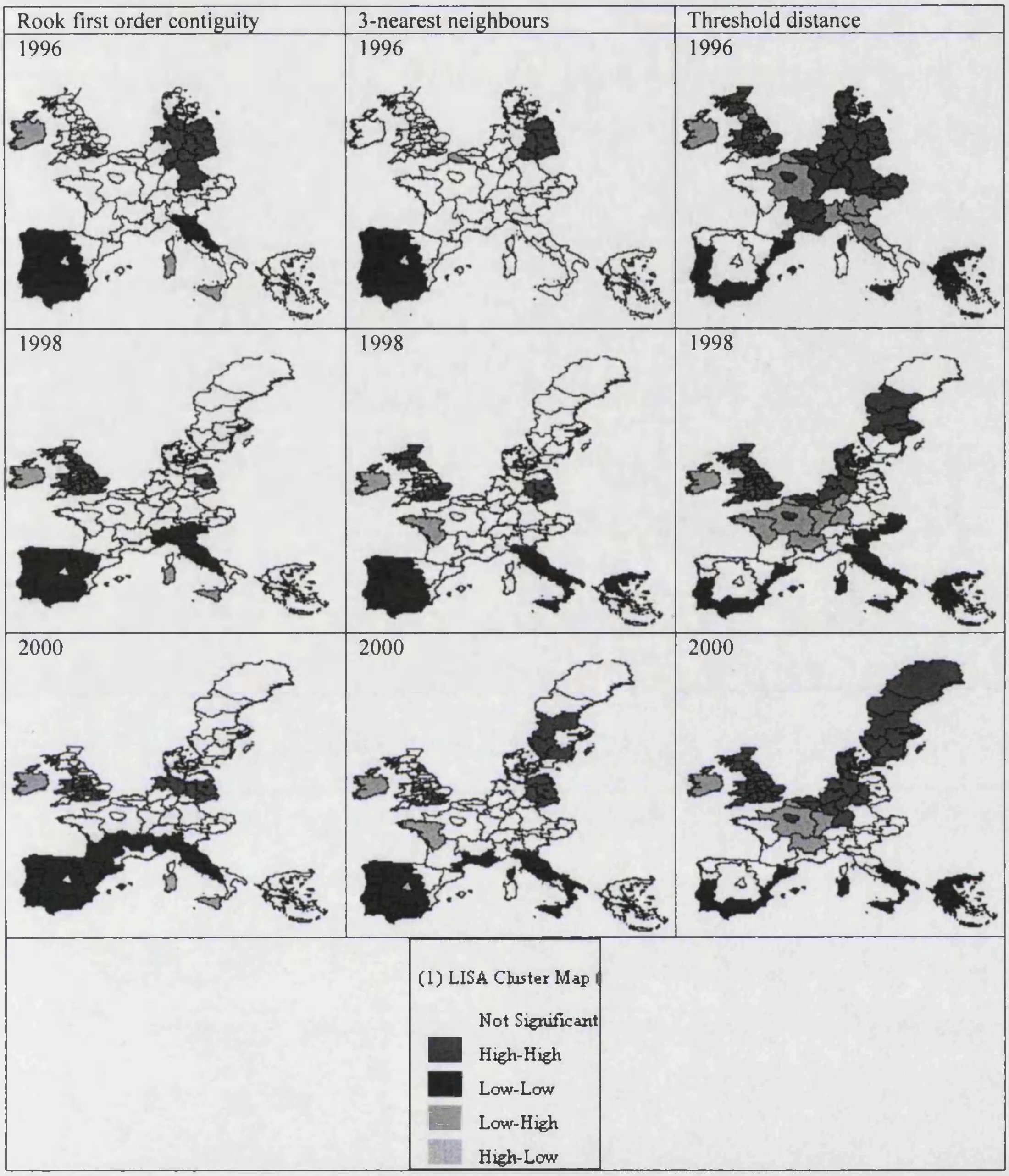
		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996												
	1997	0.6175	-0.0084	0.0776	8.0657	0.7617	-0.0119	0.0754	10.2599	0.4139	-0.0091	0.0225	18.8000
	1998	0.7313	-0.0107	0.0727	10.2063	0.8250	-0.0102	0.0747	11.1807	0.4080	-0.0096	0.0217	19.2442
	1999	0.7503	-0.0088	0.0790	9.6089	0.8002	-0.0118	0.0747	10.8701	0.3802	-0.0088	0.0226	17.2124
	2000	0.6900	-0.0039	0.0746	9.3016	0.7752	-0.0104	0.0751	10.4607	0.3968	-0.0114	0.0215	18.9860
Space-time correlation	1998												
	2000	0.6896	-0.0103	0.0725	9.6538	0.7793	-0.0106	0.0741	10.6599	0.3963	-0.0110	0.0212	19.2123
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.6109	-0.0082	0.0756	8.1892	0.7466	-0.0093	0.0768	9.8424	0.3491	-0.0115	0.0226	15.9558
	1996	0.6119	-0.0079	0.0746	8.3083	0.7433	-0.0101	0.0751	10.0320	0.3577	-0.0105	0.0225	16.3644
	1997	0.6085	-0.0068	0.0768	8.0117	0.7384	-0.0080	0.0762	9.7953	0.3619	-0.0126	0.0225	16.6444
	1998	0.7419	-0.0081	0.0772	9.7150	0.8297	-0.0072	0.0768	10.8971	0.4061	-0.0110	0.0211	19.7678
	1999	0.7607	-0.0112	0.0773	9.9858	0.8039	-0.0147	0.0749	10.9292	0.3770	-0.0118	0.0219	17.7534
	2000	0.7009	-0.0093	0.0775	9.1639	0.7776	-0.0062	0.0809	9.6885	0.3837	-0.0098	0.0234	16.8162
Space-time correlation	1998	0.5547	-0.0061	0.0676	8.2959	0.6534	-0.0100	0.0709	9.3568	0.3396	-0.0085	0.0219	15.8950
	2000	0.7029	-0.0131	0.0716	10.0000	0.7850	-0.0063	0.0729	10.8546	0.3933	-0.0119	0.0217	18.6728

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

The use of the Moran's I statistic does not allow one to assess the regional structure of human capital spatial autocorrelation. LISA are used to test the assumption of a random distribution by comparing the human capital values for each specific region with the values in the neighbouring regions (Ertur and Le Gallo, 2003). Figure 4.4 illustrates the cluster maps for average education level completed in 1996, 1998 and 2000, at three weighting schemes. They show the local variation of educational attainment in spatial autocorrelation. Different trends in human capital distribution exist across regions in the EU. The weighting schemes of the first order contiguity and the 3-nearest neighbours show that clusters of regions with poor human capital endowments are found across

Italy, in southern France (in Sud-Ouest and Centre-Est considering the first order contiguity schemes, and in Méditerranée for the 3-nearest neighbours schemes) in 2000, in Portugal and in Spain. Conversely, two clusters of regions with a high human capital stock can be found in southern England and in eastern Germany (Berlin, Brandenburg and Sachsen-Anhalt). The distance band weights schemes reveal more expanded clusters. For instance, the high-level of education cluster in the United Kingdom includes all regions in 1998 and 2000. Furthermore, many regions in Central Europe are spatial outliers, such as northern Italy in 1996, and French regions of Bassin Parisien, Nord - Pas-de-Calais, Est and Centre-Est in 1998 and 2000. Finally, this figure confirms the fact that the average education level completed is higher in northern Europe. A cluster of rich human capital regions (the north) is distinguished from a cluster of poor human capital regions (the south).

Figure 4.4: Cluster Map for Average Education Level Completed (EMN) in 1996, 1998 and 2000



Generally speaking, the results reveal the persistence of human capital disparities among the European regions over time following the patterns of urban-rural and north-south polarisation. This reveals two forms of spatial heterogeneity. In other words, the findings show that economic behaviour is not stable over space. The spatial regimes can be linked to several findings in regional development theories, such as the NEG and the cumulative causation theories, which emphasise the role of human capital spillovers in mechanisms of human capital accumulation. If one northern region acts to attract human capital, all northern regions benefit from the spillovers. Nevertheless, the spatial clustering is likely to correspond to national institutional differences. This benefit is lower for southern regions but it does exist due to the spatial multiplier effects (Anselin, 2003c). Therefore, spatial autocorrelation and spatial heterogeneity are unavoidable features of human capital variation analysis.

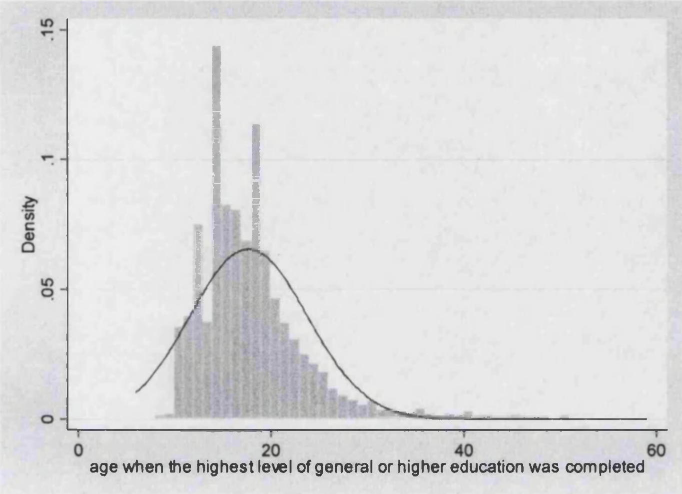
4.2.3 Average Age at which the Highest Education Level was Completed

In this subsection, ESDA on the within-region average age of respondents when the highest level of education was completed is analysed.

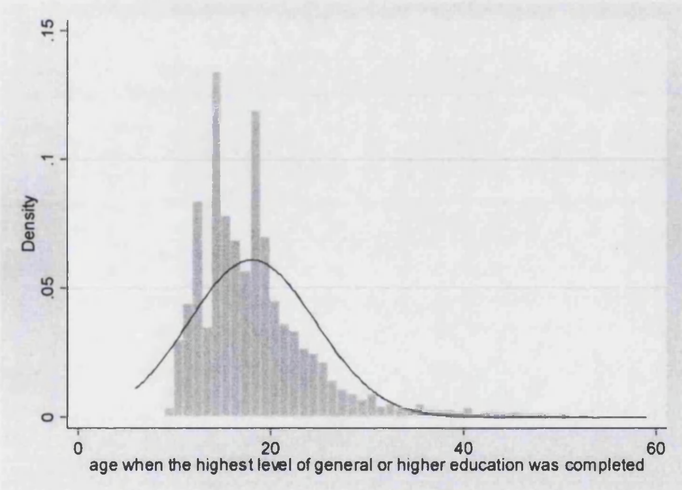
The European micro-approach of this proxy for educational attainment is illustrated by the following histograms for 1996, 1998 and 2000 (Figure 4.5). All histograms have two peaks; one at age 15 and another at age 19. This generally corresponds to the age of completion of the first and the second stage of secondary level education. Another smaller peak is found at age 13: the age at which most people have completed the primary school. After the age of 19, the European age distribution follows the normal distribution. On comparing the histograms, it is found that the peak at age 15 is lower for 1998 than for 1996, inducating that more people chose to continue their studies. Most respondents had completed their highest level of general or higher education by the time they were between 15 and 20 years old.

Figure 4.5: Histogram of Age of Respondents when their Highest Education Level was Completed

1996



1998



2000

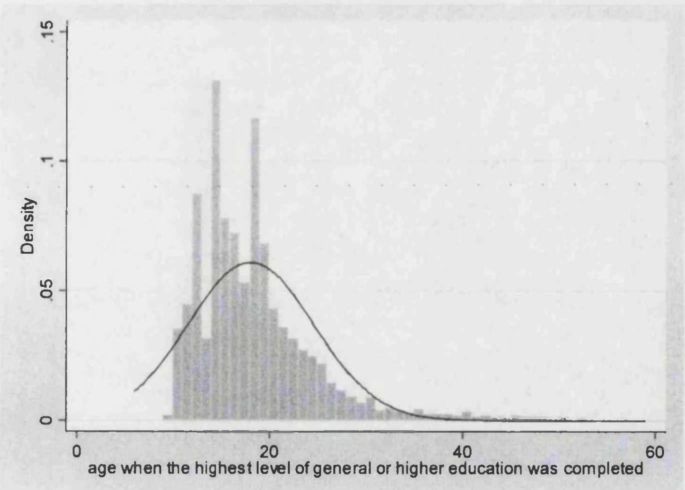


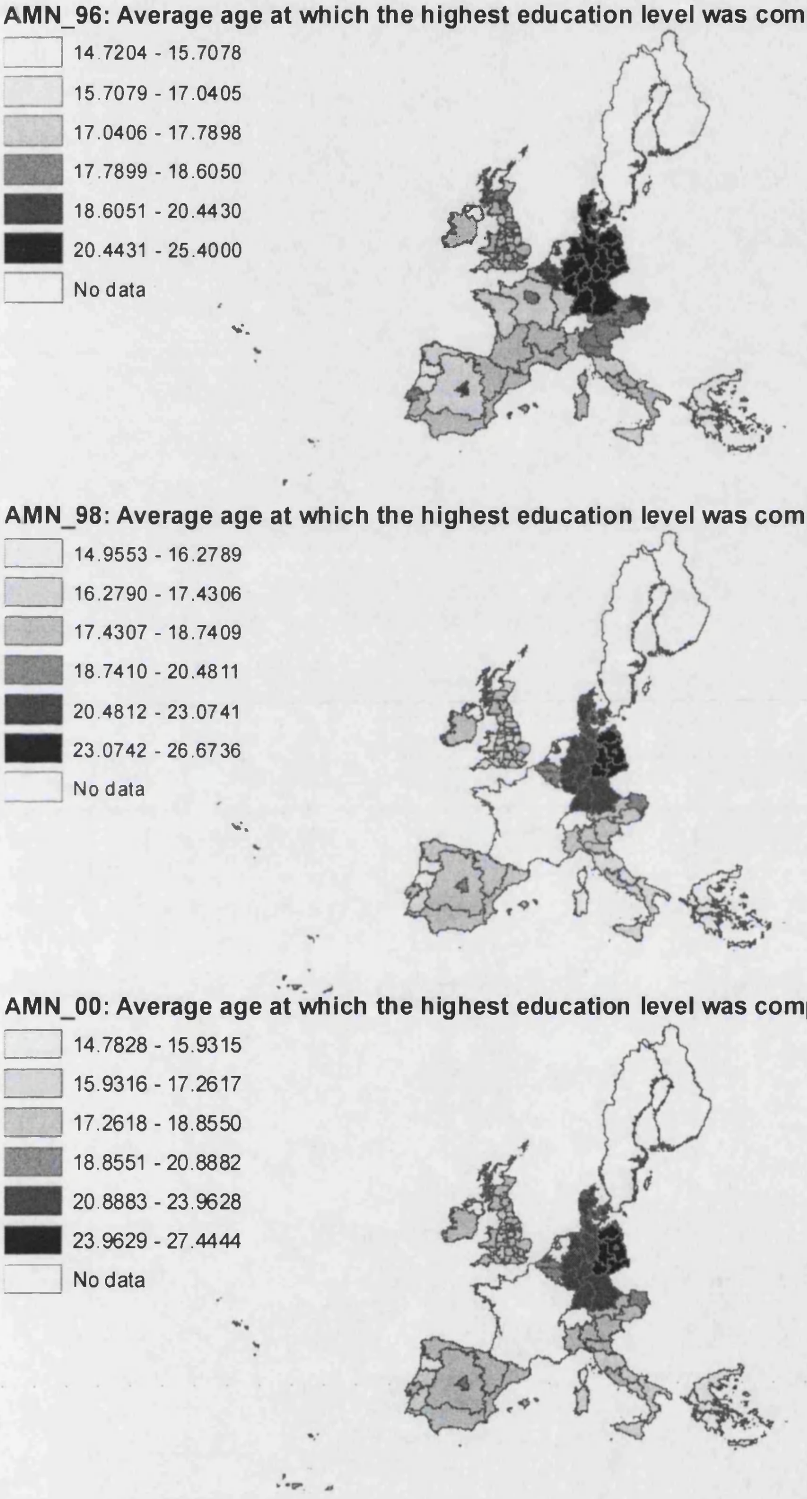
Figure 4.6 shows the regional pattern of educational attainment. Although the number of regions included in 1998 and 2000 was not satisfactory because there were no data for France, human capital endowment is seen to differ among countries and regions. The geographical distribution of European human capital endowment is expected to be highly clustered. German and Danish citizens were found to have completed their formal studies at an older age than any other European citizen. Dig a little deeper, and one will find that in Germany's schools, for instance, attendance is compulsory for all children of ages 7 to 18. For at least nine years of this period, they must attend a full-time school, and then they can choose either to continue in full-time education or to attend a vocational school part-time.[58] Taking into account the variable '*Age when full-time education was stopped*',[59] most German regions and some British ones (i.e. Berkshire, Dorset and Greater London, in 2000) register the highest average age when full-time education ceased, highlighting the high human capital endowment in those regions. Furthermore, the difference between the average age when the highest grade was completed and the average age when the full time education was stopped is higher in German regions (i.e. Sachsen, Brandenburg, Sachsen-Anhalt and Berlin, in 2000). The findings do not support the idea that the high human capital stock in Germany might be due to the large proportion of part-time students. The duration of studies in German institutions is among the longest in Europe. For instance, the nominal duration of studying physics is 5 years.[60] The spatial distribution of the average age seems to be randomly distributed across the United Kingdom regions, while in Italy and Germany it seems to be concentrated in particular areas. In Italy, there is a north-south divide, whereby high human capital endowments are concentrated in the north and, in Germany, human capital is concentrated in the eastern region. Portugal and Greece have the lowest average age on completing education in Europe. To sum up, Europe is characterised by huge disparities in the average age at which the highest level of education was completed.

[58] www.watzmann.net

[59] This variable is available for the period from 1998 to 2001.

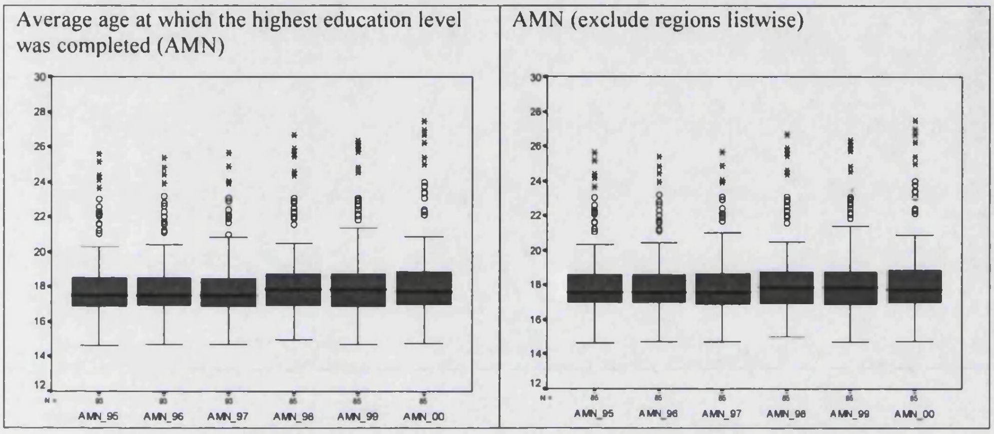
[60] www.zhr.rwth-aachen.de

Figure 4.6: Spatial Distribution of Average Age at which the Highest Education Level was Completed (AMN) in 1996, 1998 and 2000



The univariate boxplot for the average age of individuals when the highest grade was completed (Figure 4.7) shows that German regions and Denmark are outliers and extreme cases. More particularly, the educational attainment of Berlin, Brandenburg, Mecklenburg-Vorpommern and Sachsen is double the EU average. The distributions are skewed and much of the skewness is due to the outliers and extreme regions in the upper end of the distributions. The skewness is higher in 2000, indicating that people continue their studies at higher education levels. Nevertheless, the median and the box length remained the same between 1995 and 1997, and between 1998 and 2000.[61] The average increased slightly from 18.25 in 1995 to 18.81 in 2000. Finally, the distribution of this proxy for educational attainment rejects the normality assumption, because the ratio of skewness to its standard error is greater than +2, which indicates a long right tail.[62]

Figure 4.7: Boxplot for Average Age at which the Highest Education Level was Completed (AMN)



Note: extreme cases and outliers are sorted in descending order: DE3, DED, DE8, DE4, DEE, DEG, DK, DE9, DEA, DE5, DE7, DEF, DEG and DEX in 1995; DE3, DED, DE8, DE4, DEE, DEG, DK, DE9, DEA, DEF, DEF, DE2, DE5, DE6 and DEX in 1996; DE3, DED, DE8, DE4, DEE, DEG, DEF, DEK, DE9, DE5, DEA, DE7, DE2 and DEX (it is not outlier in exclude regions listwise) in 1997; DE3, DED, DE8, DE4, DEG, DEE, DE5, DE9, DEA, DE7, DEF, DE2, DEX, DE6, DK and DE1 in 1998; DED, DE3, DE8, DE4, DEE, DEG, DEF, DEA, DE5, DE7, DE9, DE2, DEX, DEK and DE6 in 1999; DED, DE3, DE8, DE4, DEE, DE5, DEG, DEA, DEF, DE2, DE9, DEX, DE7, DE6, DEK and DE1 in 2000 (see Appendix A1.1).

On the one hand, Moran's I statistics computed using the rook first order contiguity spatial weights schemes and the 3-nearest neighbours schemes are very high (Table 4.2). Thus, measuring educational attainment in terms of the average age at which the highest education level was completed has a significant positive spatial autocorrelation. The standardised values of the Moran's I statistic remained almost constant over the whole period of study. The stock of human capital endowment in a particular region may contribute to output gains in adjoining regions (Lall and Yilmaz, 2001). To put this in a slightly different way, Moran's I test statistics are likely to highlight, on the one hand, the importance of external economies that cross the weak regional boundaries (Vaya et al., 2004) and, on the other hand, the institutional differences between

[61] The median is 17.54 for 1995, 17.51 for 1996, 17.53 for 1997, 17.87 for 1998, 17.85 for 1999 and 17.73 for 2000.

[62] The ratio of skewness to standard error is 5.49 for 1995, 5.43 for 1996, 5.54 for 1997, 5.36 for 1998, 5.12 for 1999 and 5.44 for 2000.

countries that mean regions within countries are similar. Considering the space-time correlation, a region's human capital endowment in 1998 is correlated with that of its neighbouring regions in 1996 (Moran's I = 0.8026, based on the first order contiguity weights). On the other hand, constructing the threshold distance schemes, the global spatial autocorrelation is very low. For instance, Moran's I is 0.2464 in 1997.

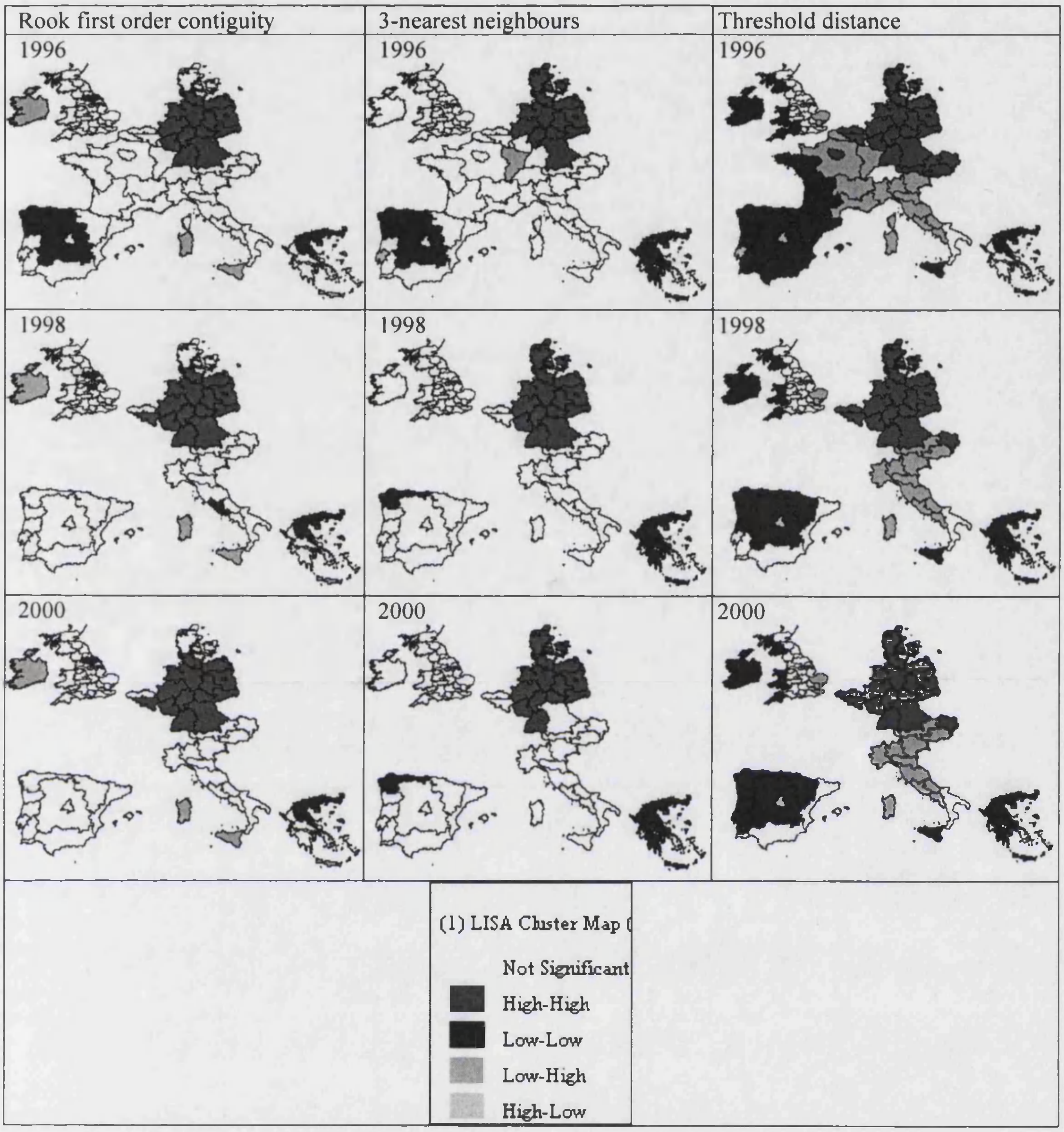
Table 4.2: Moran's I for Average Age at which the Highest Education Level was Completed (AMN)

		Excluded SE LU (E[I]=-0.0109)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.7812	-0.0083	0.0764	10.3338	0.8378	-0.0145	0.0725	11.7559	0.2465	-0.0105	0.0223	11.5247
	1996	0.7770	-0.0124	0.0763	10.3460	0.8313	-0.0120	0.0773	10.9094	0.2486	-0.0104	0.0238	10.8824
	1997	0.7872	-0.0140	0.0723	11.0816	0.8365	-0.0126	0.0763	11.1284	0.2464	-0.0105	0.0231	11.1212
	1998												
	1999												
	2000												
Space-time correlation	1998												
	2000												
		Excluded SE LU FR (E[I]=-0.0119)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.8040	-0.0120	0.0795	10.2642	0.8759	-0.0116	0.0807	10.9975	0.2912	-0.0122	0.0245	12.3837
	1996	0.8005	-0.0082	0.0800	10.1088	0.8686	-0.0133	0.0802	10.9963	0.2923	-0.0128	0.0255	11.9647
	1997	0.8093	-0.0125	0.0804	10.2214	0.8723	-0.0133	0.0806	10.9876	0.2885	-0.0120	0.0270	11.1296
	1998	0.8212	-0.0105	0.0822	10.1180	0.8983	-0.0122	0.0793	11.4817	0.2462	-0.0111	0.0256	10.0508
	1999	0.8114	-0.0108	0.0809	10.1632	0.8899	-0.0093	0.0789	11.3967	0.2457	-0.0114	0.0250	10.2840
	2000	0.8203	-0.0110	0.0819	10.1502	0.8971	-0.0122	0.0801	11.3521	0.2447	-0.0115	0.0269	9.5242
Space-time correlation	1998	0.8026	-0.0139	0.0802	10.1808	0.8717	-0.0118	0.0776	11.3853	0.2613	-0.0124	0.0252	10.8611
	2000	0.8228	-0.0092	0.0785	10.5987	0.8985	-0.0085	0.0822	11.0341	0.2474	-0.0106	0.0289	8.9273

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

Figure 4.8 illustrates the choropleth maps for educational achievement using three spatial weights schemes. The maps based on the first order contiguity weights and the 3-nearest neighbours schemes are quite similar. Low human capital endowment is concentrated in Greece (mainly in Voreia Ellada) and in Lazio (in 1998), while Germany is characterised by high human capital stock. Considering the 3-nearest neighbours spatial schemes, Noroeste is the 'core' of another cluster of low human capital endowment. The spatial distribution of educational endowment remained almost the same. The distance band schemes reveal expanded poor clusters including Portugal, Spain, western France, Greece and the western United Kingdom and, also, an expanded rich cluster including Germany and Denmark. Between the two clusters, there is a low-high cluster stretching from eastern France to Italy, in which low endowment regions are surrounded by high endowment ones.

Figure 4.8: Cluster Map for Average Age at which the Highest Education Level was Completed (AMN) in 1996, 1998 and 2000



Once again, the results reveal the persistence of human capital disparities among European regions over time, following the patterns of urban-rural and north-south polarisation. The variation in human capital endowment is influenced by region specific characteristics and the availability of highly-educated labour in neighbouring southern or northern regions. However, the pattern here is less intense than when one considers educational attainment in terms of the average education level completed.

4.2.4 The Relationship between the Two Proxies for Educational Attainment

The relationship between the average education level completed and the average age at which the highest education level was completed is explored through cross-tabulation analysis, the comparison of their boxplots (standardised distributions), the Pearson correlation and the bivariate measures of spatial association.

First, the relationship between the age of respondents when the highest education level was attained and the three levels of formal education is analysed using a cross-tabulation analysis. A categorical variable with six educational categories (age bands) is created. As stated earlier, the completion of a given educational level can be associated with somewhat different lengths of study in different countries and thus different age bands. Additionally, comparing educational attainment across countries, there is no consistent definition of either what a particular level means in terms of knowledge and skills or what a particular age band means in terms of education level completed. The duration of educational (i.e. tertiary) programmes by educational category (i.e. type of degree) differs among countries. For instance, the minimum period of registration for Bachelor students in Economics is three years full-time in the United Kingdom, while it is four years full-time in Greece. Additionally, the duration, for example, of tertiary programmes differs within countries. In Greece, the minimum period of registration for undergraduate students fluctuates from four (i.e. for those studying Economics) to six years (i.e. studying Medicine). The educational categories possibly eliminate the requirements that some knowledge and skill be demonstrated in order to pass courses and gain grades. Nor do the educational categories distinguish students by full-time or part-time registration. Therefore, in order to check the sensitivity of the results, a second categorical variable (age band) is created, which is lagged by one year of the first categorical variable. Generally speaking, in the first categorical variable, the educational categories denote:

- less than 13 (or less than 12): no education level completed;
- 13–15 (or 12–14): primary education completed;
- 16–18 (or 15–17): less than the second stage of secondary education level completed;
- 19–22 (or 18–21): the second stage of secondary education level completed;

- 23–30 (or 22–29): tertiary education level completed;
- Over 30 (or over 29): other education level completed.

Table 4.3 shows that the higher the age of respondents, the higher the education level completed. Considering the first age band, 45.95 per cent, 45.03 per cent and 44.15 per cent of respondents who had completed less than the second stage of secondary education level in 1996, 1998 and 2000, respectively, completed their formal studies when they were between 13 and 15 years old. Taking into account the second age band, 45.57 per cent, 47.02 per cent and 47.10 per cent of respondents who had completed less than the second stage of secondary education level in 1996, 1998 and 2000, respectively, completed their studies when they were between 12 and 14 years old. The largest portion of respondents who had completed the second stage of secondary education belonged to the age band 16–18 (i.e. 50.10 per cent in 1996) or 18–21 (i.e. 63.54 per cent in 1996). Finally, according to the first age band, 43.32 per cent, 45.08 per cent and 45.70 per cent of European citizens who had acquired a recognised third education level in 1996, 1998 and 2000, respectively, completed their formal studies when they were between 23–30 years of age. Considering the second age band, the largest portion were between 22–29 years old (i.e. 52.86 per cent in 1996).

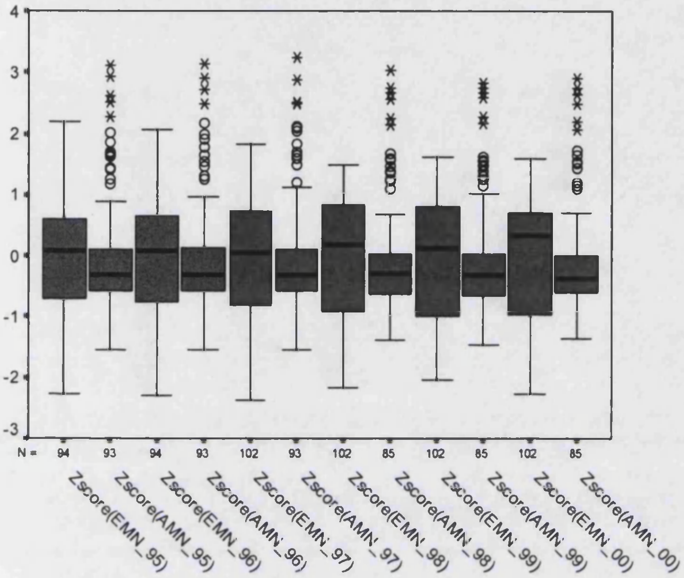
Table 4.3: Percentage of Respondents by Age Bands and Levels of Formal Education in 1996, 1998 and 2000

	1996			1998			2000		
	less than second stage of secondary education level completed	second stage of secondary education level completed	recognised third education level completed	less than second stage of secondary education level completed	second stage of secondary education level completed	recognised third education level completed	less than second stage of secondary education level completed	second stage of secondary education level completed	recognised third education level completed
<13	27.39	0.17	0.03	30.05	0.07	0.01	32.06	0.13	0.01
13-15	45.95	2.02	1.51	45.03	0.93	2.15	44.15	1.19	2.38
16-18	19.31	50.10	9.91	17.46	45.22	11.44	17.49	45.02	11.74
19-22	3.22	35.46	37.32	3.34	37.75	31.38	2.61	38.21	29.77
23-30	1.84	7.51	43.32	1.70	9.74	45.08	1.64	9.56	45.79
30>	2.28	4.75	7.90	2.42	6.30	9.92	2.04	5.89	10.31
<12	13.95	0.08	0.02	14.40	0.02	0.01	15.56	0.04	0.01
12-14	45.57	0.75	0.40	47.02	0.23	0.44	47.10	0.36	0.40
15-17	29.75	20.16	6.24	27.88	13.42	8.52	28.21	12.77	9.59
18-21	6.19	63.54	30.57	6.11	66.62	25.11	5.07	67.98	23.50
22-29	2.00	10.00	52.86	1.89	12.42	53.66	1.73	11.99	53.90
29>	2.55	5.47	9.91	2.69	7.30	12.27	2.32	6.86	12.60

Second, considering the univariate boxplots of proxies for educational attainment (Figure 4.9), the median gap between the two proxies becomes even higher from one time period to the next. This probably depicts the decreasing correlation between the two proxies through time for regions that are close to the European average.

Additionally, the distributions for the average education level completed are more skewed than those for the average age at which the highest education level was attained, due to the outliers and extreme values. In 2000, the distribution of the average age is skewed on the left.

Figure 4.9: Boxplot for Standardised (Zscore) Average Education Level Completed (EMN) and Average Age at which the Highest Education Level was Completed (AMN)



Note: extreme cases and outliers are sorted in descending order: DE3, DED, DE8, DE4, DEE, DEG, DK, DE9, DEA, DE5, DE7, DEF, DEG and DEX in 1995; DE3, DED, DE8, DE4, DEE, DEG, DK, DE9, DEA, DEF, DEF, DE2, DE5, DE6 and DEX in 1996; DE3, DED, DE8, DE4, DEE, DEG, DEF, DEK, DE9, DE5, DEA, DE7, DE2 and DEX in 1997; DE3, DED, DE8, DE4, DEG, DEE, DE5, DE9, DEA, DE7, DEF, DE2, DEX, DE6, DK and DE1 in 1998; DED, DE3, DE8, DE4, DEE, DEG, DEF, DEA, DE5, DE7, DE9, DE2, DEX, DEK and DE6 in 1999; DED, DE3, DE8, DE4, DEE, DE5, DEG, DEA, DEF, DE2, DE9, DEX, DE7, DE6, DEK and DE1 in 2000 (see Appendix A1.1).

Third, on measuring the Pearson index, a positive linear correlation is shown. This correlation is higher between 1995 and 1997 than for 1997 and 1998 (Table 4.4).

Table 4.4: Pearson correlation between two proxies for educational attainment

	1995	1996	1997	1998	1999	2000
EMN-AMN	0.730 (0.000)** 85	0.710 (0.000)** 85	0.692 (0.000)** 85	0.298 (0.000)** 85	0.269 (0.013)* 85	0.453 (0.000)** 85
	0.711 (0.000)** 93	0.695 (0.000)** 93	0.672 (0.000)** 93			

Note: ** correlation is significant at the 0.01 level (2-tailed); * correlation is significant at the 0.05 level (2-tailed).

Fourth, the correlation between the average education level completed within a region and the average age at which the highest education level was completed in neighbouring regions, and vice versa, are explored. In 1996, for instance, the bivariate Moran's I statistic between the average education level completed within a region and the average age of neighbouring regions is 0.4534, while that between the average age within a region and the average education level completed of neighbouring regions is 0.4918, for the first order contiguity spatial weights schemes, 0.5428 and 0.5457, respectively, for the 3-nearest neighbours weights schemes, and 0.2129 and 0.2140, respectively, for the threshold distance band weights schemes. No matter what proxy for educational attainment is used, geographical location is important in accounting for the human capital performance of the regions due to the spatial interactions that occur between regions. The spatial distribution of education stock seems to be far from random.

4.3 Defining and Measuring Educational Inequality

This section explores the formal definition and measurement of the two proxies for educational inequality. The first subsection focuses on the recent definitions of educational inequality; the second explores inequality in terms of education level completed; and the third analyses inequality in terms of the age at which the highest education level was completed. The second and the third subsections also place an emphasis on the role of spatial effects. The fourth subsection represents the within-region educational inequality as major component of the educational inequality in Europe, and the fifth examines the relationship between the two proxies.

4.3.1 A Formal Definition of Educational Inequality

The 'relative' measures of educational inequality have been used in many studies before (Marin and Psacharopoulos, 1976; Winegarden, 1979; Ram, 1990). In the work of Ram (1990), for example, educational inequality is represented by the standard deviation of the educational distribution for each observation. However, more recent studies use 'relative' measures of educational inequality (i.e. Cornia et al., 2001; Thomas et al., 2001; Castello and Domenech, 2002; De Gregorio and Lee, 2002). Castello and Domenech (2002), for instance, taking school attainment levels, computed the Gini coefficient. Thomas et al. (2001) measure inequalities in educational attainment using the education Gini and Theil indices.

In this study, educational inequality is measured using the formula of income inequality indices: the relative mean deviation index, the Gini coefficient, the generalised entropy index and the Atkinson index. As in the measures of educational attainment, two proxies for educational inequality are presented.

The first proxy is inequality in education level completed. It is collected using the same variable used to measure the average education level completed (*'Highest level of general or higher education completed'*).[63] The Theil index takes as its minimum value (0) when the entire population is concentrated in a single educational category, while it takes as its maximum one ($\log N$) when the entire population belongs to the category of less than the second stage of secondary education level completed (S_3), except for one person alone, who has a recognised tertiary level qualification.

The second proxy is inequality in the age at which the highest education level was completed and is collected using the same variable used to measure the average age at which the highest grade was completed (*'Age at which the highest level of general or higher education was completed'*).[64] Educational inequality is zero when and only when

---

[63] Consider a population of individuals $i \in \{1,2,\ldots,N\}$, where each person is associated with a unique value of the measured formal education level completed. It has been assumed that

$$y = \begin{cases} 0 \textit{ for less than } \sec ond \textit{ stage of } \sec ondary \textit{ education level completed} \\ 1 \textit{ for } \sec ond \textit{ stage of } \sec ondary \textit{ education level completed} \\ 2 \textit{ for recognised third education level completed} \end{cases}$$ such that

$\sum_{i=1}^{N} y_i \equiv Y^{63}$. I define the education level completed ratio r_i as the ratio of y_i to the average $\overline{Y}$ ($\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} y_i = \frac{Y}{N}$) $r_i = y_i / \overline{Y}$. By definition, educational equality exists when any education level completed is equally distributed across all persons (all persons hold the same higher degree). Hence, educational inequality is zero when and only when $r_i = 1.0$ for all i; otherwise, inequality is greater than zero. Conceptualising inequality in the education level completed as the average disproportionality across all persons implies that the degree of inequality depends on the average distance of the education level completed ratios r_i from 1.0. Educational inequality is unaffected by proportional increases or decreases. Inequality indices ($EINEQ$) can be expressed in a common form $EINEQ = \frac{1}{N}\sum_{i=1}^{N} f(r_i)$, where f denotes the disproportionality or distance function which captures the mathematical functions for determining deviations of education level completed ratios from 1.0. For instance, using the formula of income Theil entropy index ($GE1$), inequality in education level completed is defined as $EGE1 = \sum_{i=1}^{N} z_i \log(Nz_i)$, where z_i is the human capital share, that is individual i's higher education level completed as a proportion of total human capital for the entire regional population.

[64] This index ($AINEQ$) can be expressed in the form $AINEQ = \frac{1}{N}\sum_{i=1}^{N} f(r_i)$, where f denotes the distance function which captures the mathematical functions for determining deviations of ratios of age at which the highest education level was completed from 1.0. Using, once again, the formula of income

all people have completed their highest education level at the same age; otherwise, inequality is greater than zero.

4.3.2 *Inequality in Education Level Completed*

Inequality in the education level completed is measured by the Gini index ($EGINI$), the relative mean deviation index ($ERMD$), the generalised entropy index for two different parameters ($EGE1$ when $a=1$, and $EGE2$ when $a=2$) and the Atkinson index for one parameter only ($EA050$ when $\varepsilon=0.50$).

Considering the geographical distribution of the Gini coefficient on education level completed in 1996, 1998 and 2000 (Figure 4.10), there are striking differences in educational inequality within regions between different parts of the EU. Inequality in human capital endowments is higher in southern Europe — extending from Greece to Italy, Spain and Portugal — than it is in the northern periphery. The within-region human capital inequality is typically half of the EU average in Germany, Denmark and Sweden. The EU north-south divide indicates that regional economies within the southern group seem to interact more with one another than those outside.

The short trends in the evolution of inequality in the education level completed demonstrate that inequality remained almost constant, except in France and Italy, where it increased even further in 1998 and 2000.

Considering the urbanisation level of each region, educational inequality is lower in the northern metropolitan areas such as London, Paris, Hamburg and Brussels, as well as in metropolitan areas in the south, such as Madrid, Lisbon and Athens. Additionally, inequality is lower in the metropolises than in the remainder of the respective countries. Highly-educated workers from rural areas are likely to move to core cities in order to achieve promotion and greater employment returns. The urban market seems able to attract and retain high quality students and workers. Better educated people move to large cities in search of employment and higher standards of living. Individuals with higher levels of human capital tend to be migrate more. The northern metropolitan areas

---

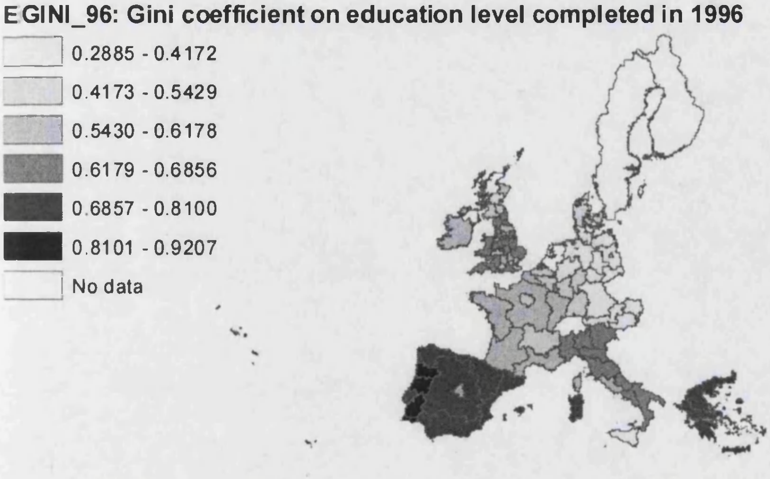
Theil entropy index ($GE1$), inequality in age at which the highest education level was completed is defined as $AGE1=\frac{1}{N}\sum_{i} r_i \log(r_i)$.

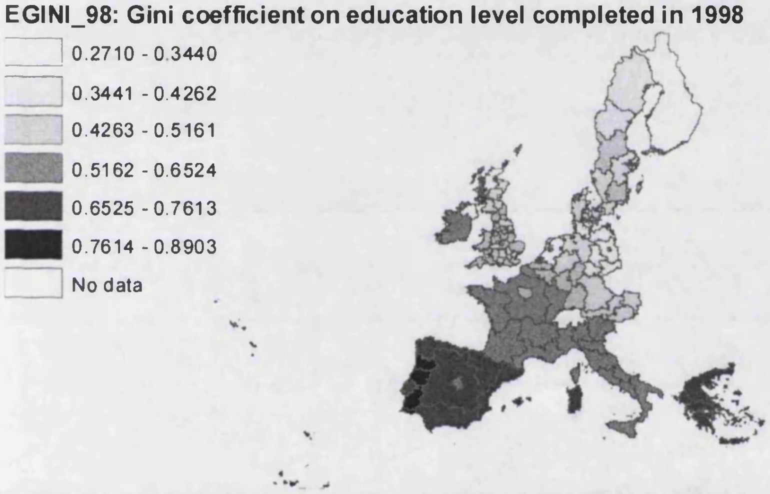
acquire the most-educated segment of the EU population. Therefore, urbanisation seems to generate new requirements for the development of higher education.

To sum up, the EU north-south divide and the degree of urbanisation seem to have an effect on educational inequality. The geographical distributions of other measures of inequality such as the relative mean deviation index, the Theil index, the squared coefficient of variation and the Atkinson index yield similar results.[65]

[65] The results are provided upon request.

Figure 4.10: The Spatial Distribution of the Gini Coefficient on Education Level Completed (EGINI) in 1996, 1998 and 2000





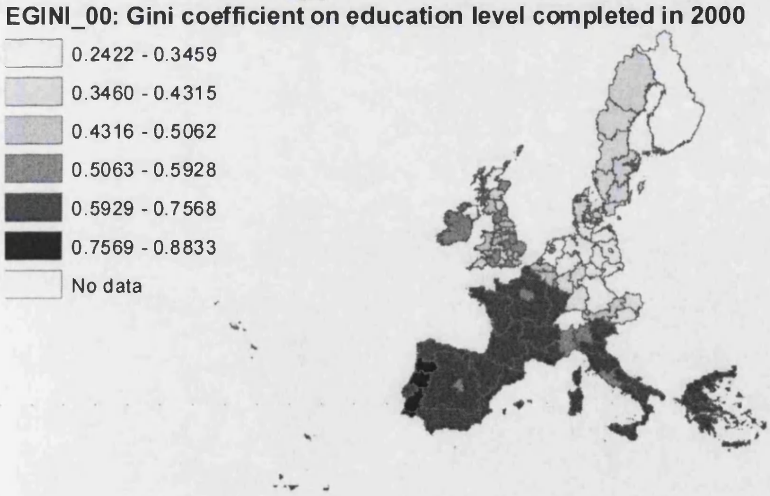
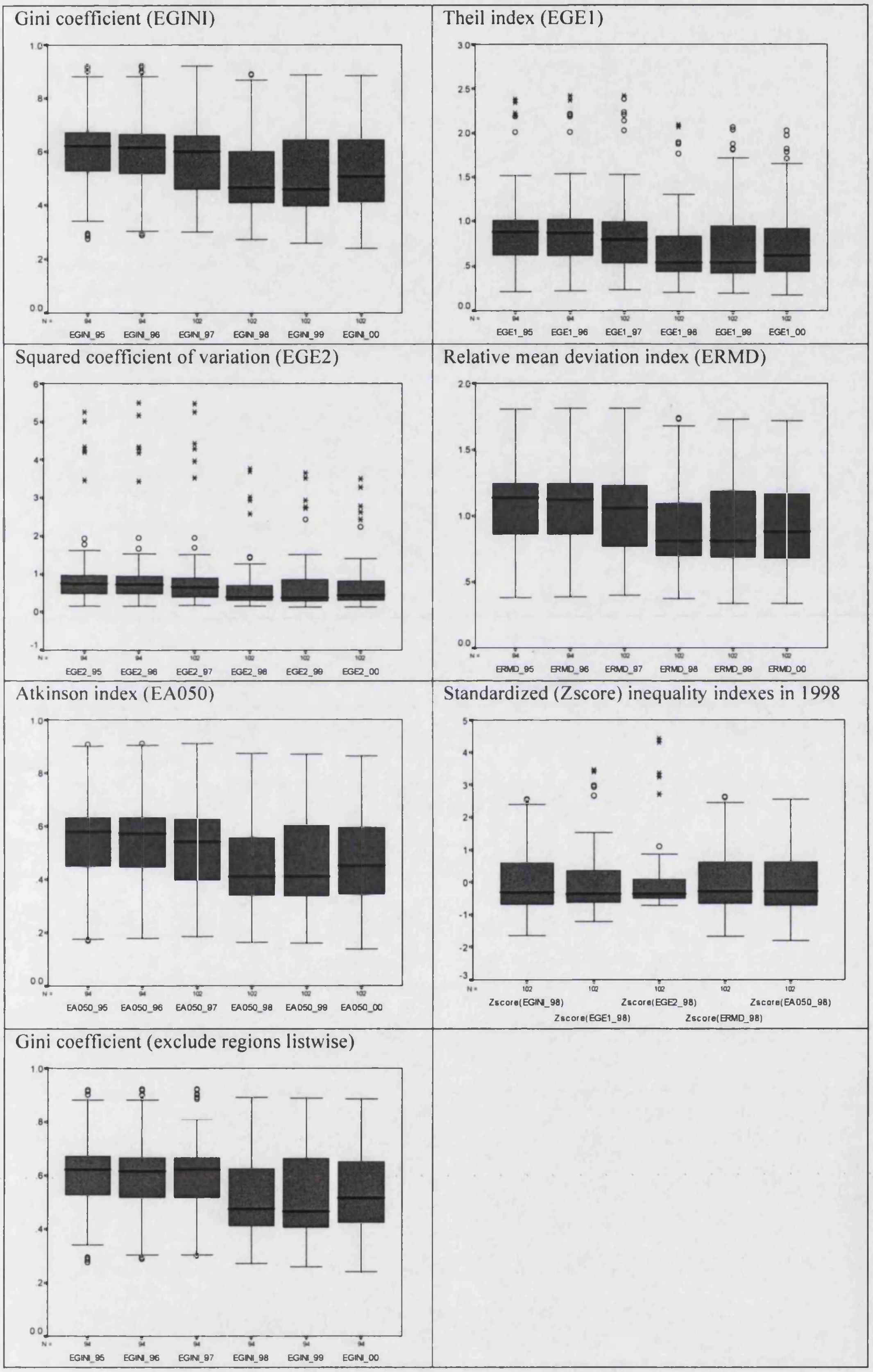


Figure 4.11, which presents the univariate boxplots of the Gini coefficient on education level completed, shows that the Portuguese regions of Norte, Centro, Alentejo and Algarve are outliers from the upper edge of the box, while levels of educational inequality within Sachsen and Thüringen are between 1.5 and 3 box lengths from the lower edge. The univariate boxplots of the generalised entropy indices (the Theil index

and the squared coefficient of variation) reveal many outliers and extreme regions. For instance, Açores, Madeira, Centro (PT), Alentejo and Algavre emerge as extreme regions using the Theil index for 1995. The Portuguese regions are either outliers or extreme cases. Considering the squared coefficient of variation, there are many extreme regions. Their value is very high and they represent the Portuguese regions alone. The Spanish region of Centro is also an outlier over the period 1995–1998. The distributions of the relative mean deviation index are less skewed, because two regions are outliers (Açores and Alentejo) in 1998 only. The distributions of the Atkinson index are compact as well. Madeira and Açores are outlying observations at the higher end of the distribution in 1995 and 1996, respectively; and Hamburg, Brandenburg, Sachsen and Sachsen-Anhalt are outlying regions in the lower end of the distribution. Final, for all educational inequality indices, the median and the average decreased considerably from 1997 to 1998. For instance, the mean and the average of the Gini coefficient decreased by 0.07 and 0.13, respectively.

Figure 4.11: Boxplot for Inequality Indices on Education Level Completed



Note: extreme cases and outliers are sorted in descending order:
EGINI: PT3, PT2, PT15 and PT14 (upper end); DE4, DEE, DED and DEG (lower end) in 1995; PT2, PT3, PT12, PT14, PT15 and PT11 (upper end); DED and DEG (lower end) in 1996; PT14 and PT12 (upper end) in 1998.

EGE1: PT3, PT2, PT15, PT14 and PT11 (upper end) in 1995; PT2, PT3, PT12, PT14, PT15 and PT11 (upper end) in 1996; PT2, PT3, PT14, PT12, PT15 and PT11 (upper end) in 1997; PT14, PT2, PT12, PT15, PT3 and PT11 (upper end) in 1998; PT2, PT14, PT12, PT3 and PT15 (upper end) in 1999; PT2, PT14, PT15, PT12 and PT3 (upper end) in 2000.
EGE2: PT3, PT2, PT15, PT14, PT12, PT11, PT13 and ES4 (upper end) in 1995; PT2, PT3, PT12, PT14, PT15, PT11, PT13 and ES4 (upper end) in 1996; PT2, PT3, PT14, PT12, PT15, PT11, PT13 and ES4 (upper end) in 1997; PT14, PT2, PT12, PT15, PT3, PT11, ES4 and PT13 (upper end) in 1998; PT2, PT14, PT12, PT3, PT15 and PT11(upper end) in 1999; PT2, PT14, PT15, PT12, PT3, PT11 (upper end) in 2000.
ERMD: PT14 and PT2 (upper end) in 1998.
EA050: PT3 (upper end); DE4, DED and DEG (lower end) in 1995; PT2 (upper end) in 1996.
EGINI (exclude regions listwise): PT3, PT2, PT15 and PT14 (upper end); DE4, DEE, DED and DEG (lower end) in 1995; PT2, PT3, PT12, PT14, PT15 and PT11 (upper end); DED and DEG (lower end) in 1996; PT2, PT3, PT14, PT12, PT15 and PT11 (upper end); DED (lower end) in 1997 (see Appendix A1.1).

The distributions of educational inequality indices are comparable only when they are measured on the same scale. Considering the boxplots of the standardised educational inequality indices in 1998 (Figure 4.11), the distributions of the Gini coefficient, the relative mean deviation index and the Atkinson index are quite similar to one another and are the most compact. The normality assumption is rejected for all distributions, because the ratio of skewness to their standard error is greater than +2, which indicates a long right tail.[66] Table 4.5 shows the Pearson correlation of the above indices for 1998. Correlations are high and up to 0.861. They are also significant at the 0.01 level (2-tailed) and at the first three decimals.

Table 4.5: Pearson Correlations among Inequality Indices for Education Level Completed in 1998

	EGINI	EGE1	EGE2	ERMD	EA050
EGINI	1	0.966 (0.000)** 102	0.867 (0.000)** 102	0.985 (0.000)** 102	0.990 (0.000)** 102
EGE1		1	0.963 (0.000)** 102	0.971 (0.000)** 102	0.965 (0.000)** 102
EGE2			1	0.874 (0.000)** 102	0.861 (0.000)** 102
ERMD				1	0.996 (0.000)** 102
EA050					1

Note: ** correlation is significant at the 0.01 level (2-tailed).

The next step is to identify global and local spatial autocorrelation so as to characterise the pattern in the location of inequalities in educational attainment in the EU and the way that this pattern has probably changed over the period 1995–2000. Due to the high correlation among the inequality indices for education level completed, I only present the spatial autocorrelation analysis for the Gini coefficient. First of all, the Moran's I statistics computed using the rook first order contiguity spatial weights matrices over the period 1995–2000 show a significant positive spatial autocorrelation (Table 4.6). This is likely to test theory of the interregional interaction through educational

[66] The ratio of skewness to standard error is 2.97 for the Gini coefficient, 7.48 for the Theil index, 12.41 for the squared coefficient of variation, 3.47 for the relative mean deviation index and 3.64 for the Atkinson index.

externalities. The space-time correlations are also high. For instance, the Moran's I statistic between the within-region inequality in 2000 and the inequality of neighbouring regions in 1998 is 0.6809. Taking into account the 3-nearest neighbours spatial weights schemes, Moran's I statistics are high over the period 1995–2000. Finally, the Moran's I statistics based on the distance band are much lower than the previous schemes, but remain significant. The trends in the evolution of the standardised Moran's I statistics are quite similar. They show a significant global tendency toward the spatial clustering of similar regions in terms of educational inequality.

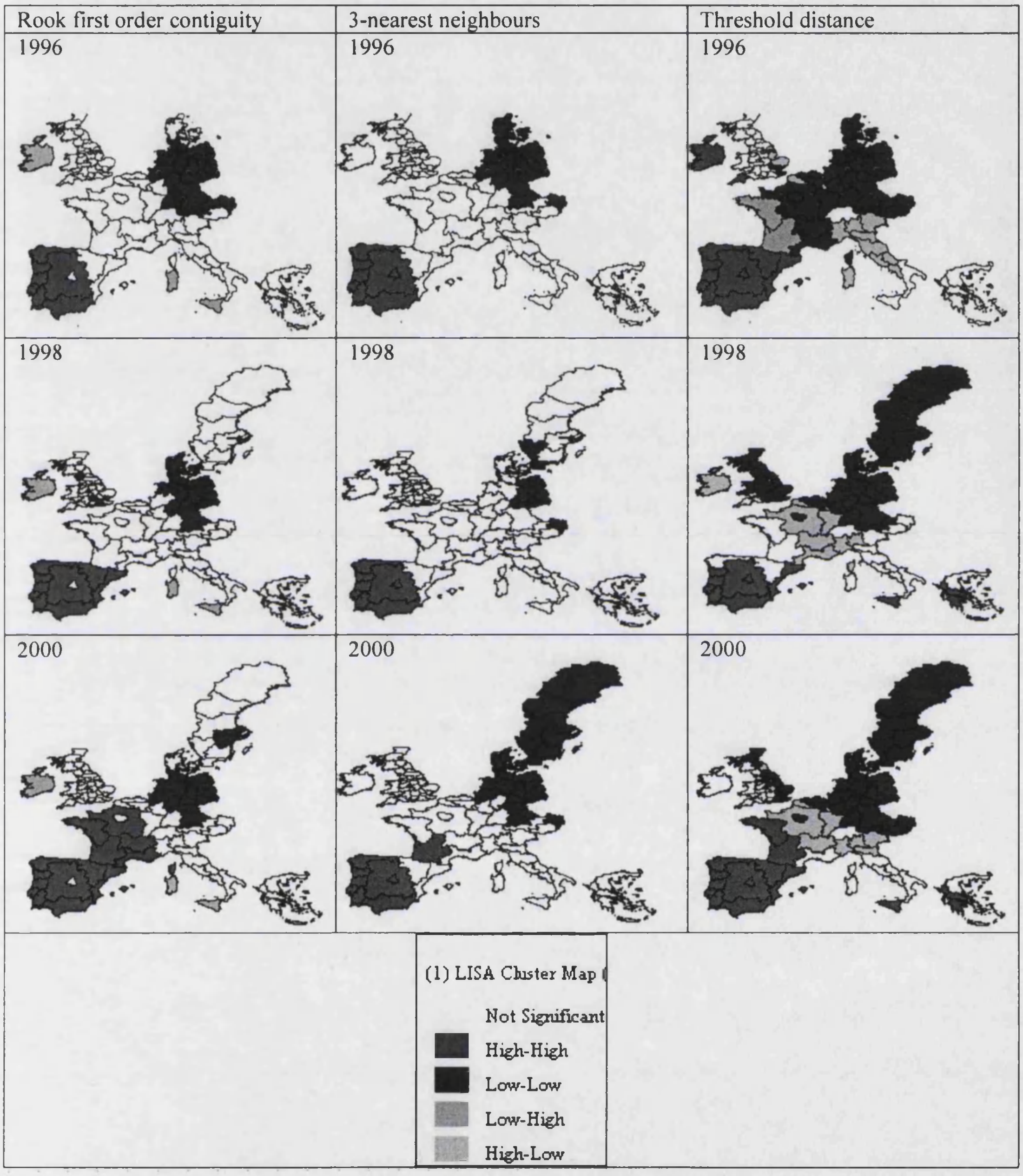
Table 4.6: Moran's I for the Gini Coefficient on Education Level Completed (EGINI)

		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995												
	1996												
	1997	0.6906	-0.0050	0.0741	9.3873	0.7983	-0.0089	0.0744	10.8495	0.4686	-0.0097	0.0228	20.9781
	1998	0.7063	-0.0090	0.0748	9.5628	0.8217	-0.0076	0.0721	11.5021	0.4643	-0.0101	0.0219	21.6621
	1999	0.7224	-0.0104	0.0741	9.8893	0.7619	-0.0078	0.0742	10.3733	0.3943	-0.0107	0.0216	18.7500
	2000	0.7195	-0.0100	0.0777	9.3887	0.7803	-0.0069	0.0743	10.5949	0.4212	-0.0094	0.0223	19.3094
Space-time correlation	1998												
	2000	0.6809	-0.0070	0.0736	9.3465	0.7716	-0.0084	0.0702	11.1111	0.4301	-0.0102	0.0213	20.6714
		Excluded SE (E[I]=-0.0108)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.7229	-0.0102	0.0769	9.5332	0.8223	-0.0125	0.0767	10.8840	0.3889	-0.0100	0.0223	17.8879
	1996	0.6995	-0.0101	0.0749	9.4740	0.7913	-0.0121	0.0789	10.1825	0.3783	-0.0111	0.0235	16.5702
	1997	0.6764	-0.0107	0.0740	9.2851	0.7730	-0.0102	0.0745	10.5128	0.3892	-0.0115	0.0227	17.6520
	1998	0.7124	-0.0098	0.0756	9.5529	0.8195	-0.0123	0.0782	10.6368	0.4370	-0.0110	0.0229	19.5633
	1999	0.7257	-0.0088	0.0726	10.1171	0.7535	-0.0092	0.0766	9.9569	0.3558	-0.0119	0.0225	16.3422
	2000	0.7204	-0.0069	0.0719	10.1154	0.7692	-0.0135	0.0771	10.1518	0.3632	-0.0107	0.0217	17.2304
Space-time correlation	1998	0.5713	-0.0070	0.0661	8.7489	0.6689	-0.0096	0.0717	9.4630	0.3566	-0.0084	0.0210	17.3810
	2000	0.6843	-0.0068	0.0758	9.1174	0.7653	-0.0075	0.0750	10.3040	0.3922	-0.0102	0.0220	18.2909

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

Once again, LISA is required in order to compare the human capital inequality values for each specific region with the values for the neighbouring regions. Figure 4.12 depicts the cluster map for the Gini coefficient on educational inequality in 1996, 1998 and 2000 at three weights schemes. The cluster maps of the first order contiguity scheme and the 3-nearest neighbours scheme are quite similar. Portugal and Spain include clusters of regions with high educational inequality, while Germany and Denmark include clusters with low human capital inequality. In 2000, both types of clusters have expanded further to include some western French regions (i.e. Sud-Ouest) into the high inequality human capital cluster and some Swedish regions (i.e. Östra Mellansverige) into the low inequality cluster. Considering the distance band weights schemes, the clusters are evenly spread out and also are separated by a buffer zone which includes at least the regions of Bassin Parisien, Nord–Pas-de-Calais, Est, Centre-Est, Nord Ovest and Lombardia in 1998 and 2000.

Figure 4.12: Cluster Map for the Gini Coefficient on Education Level Completed (EGINI) in 1996, 1998 and 2000



The cluster maps highlight some spatial heterogeneity hidden within the global spatial autocorrelation pattern. This may indicate the coexistence of two distinct spatial regimes. Firstly, urbanisation seems to be negatively correlated with human capital inequality, because it is lower in the metropolises. Secondly, there is empirical evidence of an EU north-south divide. Homogeneity is higher among the northern regions of the EU, as well as among the southern ones, but not between regions in the north and south.

Although all regions benefit from the diffusion of human capital that results from spatial multiplier effects, that diffusion seems to be easier within groups of closely related economies (Vaya et al., 2004). The responses to changes in educational inequality over the period 1995-2000 remained almost constant, demonstrating the persistence of inequality and its dynamic process.

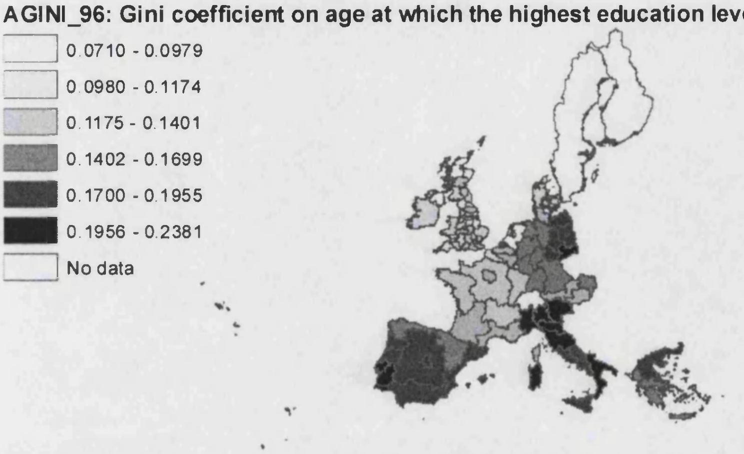
4.3.3 Inequality in the Age at which the Highest Education Level was Completed

The spatial distribution of educational inequality within regions when it is measured in terms of inequality in the age at which the highest education level was completed seems to be different from that of inequality in education level completed. In both cases, however, the geographical distribution appears to be far from random or equal. According to Figure 4.13, the Gini coefficient is almost double the EU average in northern Italy (Nord Ovest, Lombardia, Nord Est and Emilia-Romagna), in southern Portugal (Lisboa, Alentejo and Algarve) and in the German regions of Brandenburg and Sachsen. Another important characteristic shown in this figure is the within-country disparities of the Gini coefficient. In Portugal, Spain, Italy and Germany, regional disparities fluctuate at high Gini coefficient levels, while in the United Kingdom and France the coefficient remains low. The above argument highlights the importance of the within-country disparities in inequalities on considering a broader concept of human capital, which is likely to encompass experience, learning-by-doing and on-the-job training from a more positive viewpoint, and unemployment and economic inactivity period from the negative viewpoint. The geographical distributions of other measures of inequality such as the relative mean deviation index, the Theil index, the squared coefficient of variation and the Atkinson index yield similar results.[67] To sum up, educational inequality seems to be concentrated in particular regions of the EU.

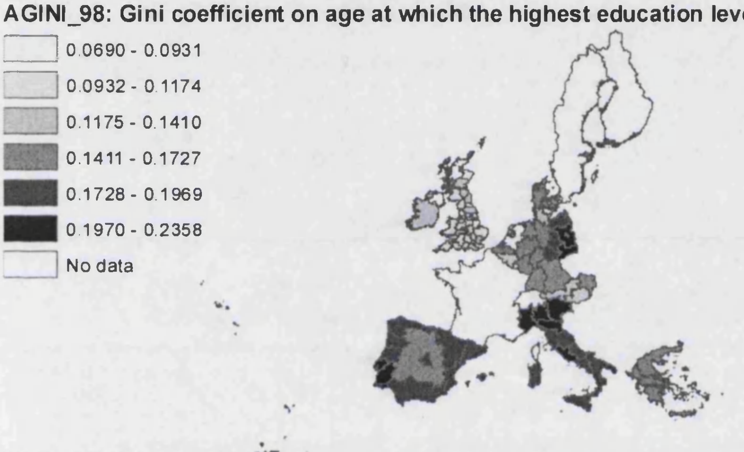
[67] The results are provided upon request.

Figure 4.13: Spatial Distribution of the Gini Coefficient on Age at which the Highest Education Level was Completed (AGINI) in 1996, 1998 and 2000

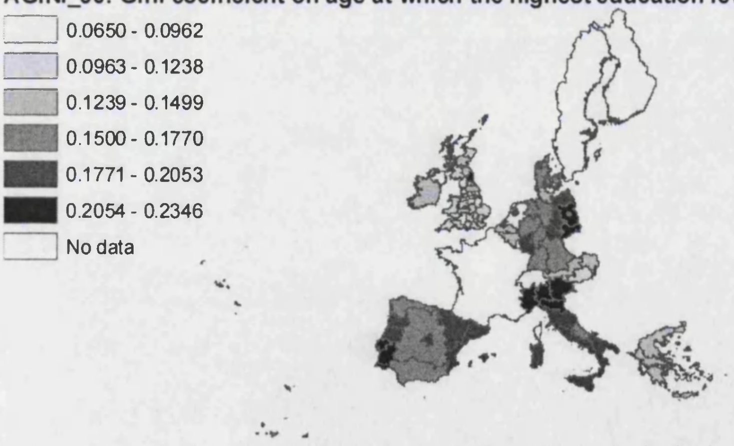
AGINI_96: Gini coefficient on age at which the highest education level was completed in 1996



AGINI_98: Gini coefficient on age at which the highest education level was completed in 1998

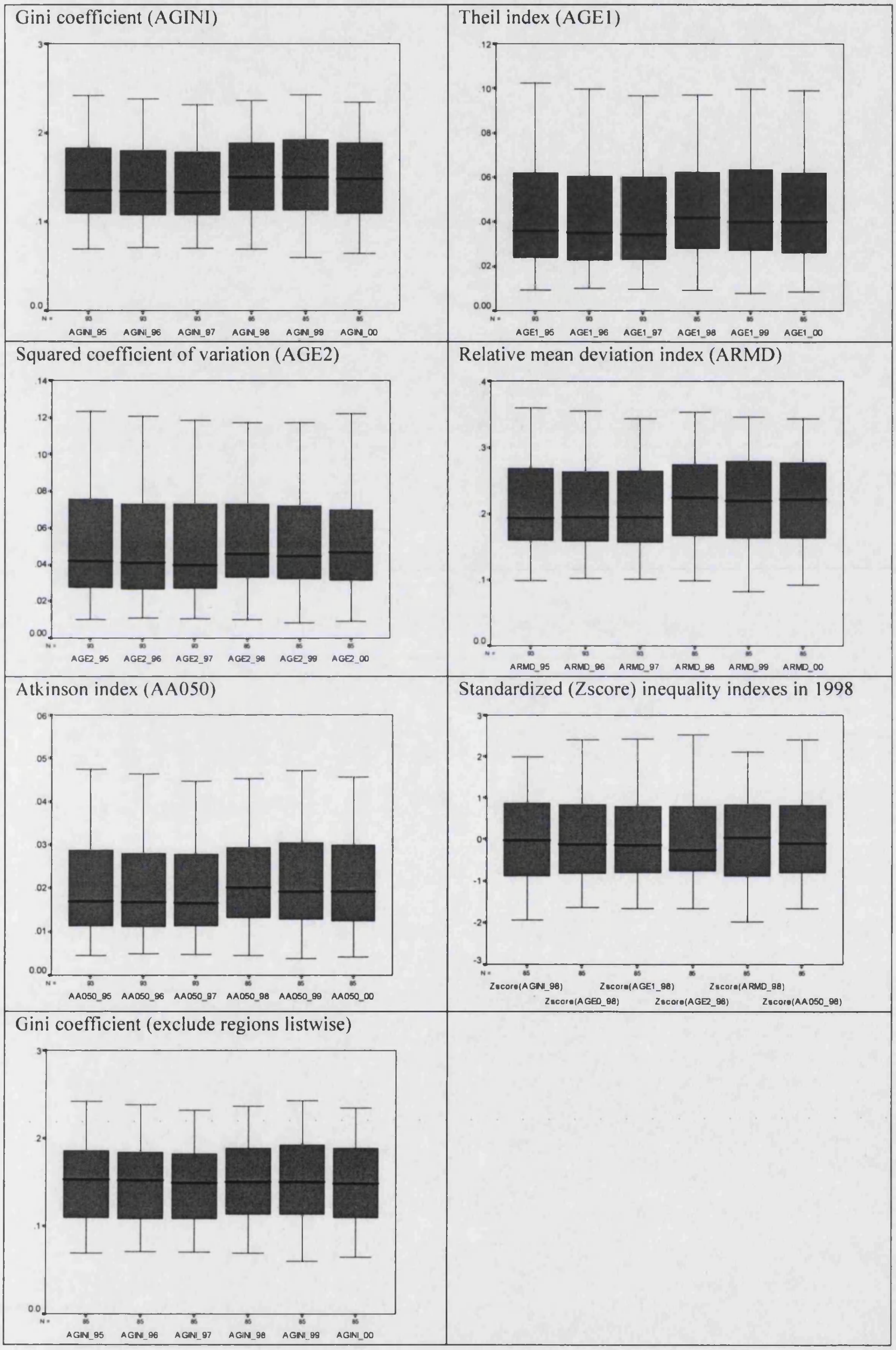


AGINI_00: Gini coefficient on age at which the highest education level was completed in 2000



Once again, the boxplot for inequality in human capital will reveal more about the data (Figure 4.14). All distributions referring to the age at which the highest education level was attained are fairly compact, because the whiskers are, in fact, the extreme values. Furthermore, the interquartile range seems to be constant between 1995 and 1997, and between 1998 and 2000.

Figure 4.14: Boxplot for Inequality Indices on Age at which the Highest Education Level was Completed



The boxplots of standardised education inequality indices for 1998 (Figure 4.14) demonstrate that the distributions of the Gini coefficient and the relative mean deviation index exhibit the greatest difference between the first and third quartiles. Additionally, they are similar to one another in terms of their compactness. The normality assumption is accepted for the Gini coefficient, the relative mean deviation and the Atkinson distribution, because the ratio of skewness to their standard error is greater than -2 and less than +2, but it is rejected for the generalised entropy indices (the Theil index and the squared coefficient of variation).[68] Table 4.7 shows the Pearson correlation among these indices for 1998. The correlations are high and up to 0.94. They are also significant at the 0.01 level (2-tailed) and to the first three decimals.

Table 4.7: Pearson Correlations among Inequality Indices on Age at which the Highest Grade was Completed in 1998

	AGINI	AGE1	AGE2	ARMD	AA050
AGINI	1	0.980 (0.000)** 85	0.962 (0.000)** 85	0.992 (0.000)** 85	0.966 (0.000)** 85
AGE1		1	0.996 (0.000)** 85	0.966 (0.000)** 85	0.970 (0.000)** 85
AGE2			1	0.944 (0.000)** 85	0.959 (0.000)** 85
ARMD				1	0.948 (0.000)** 85
AA050					1

Note: ** correlation is significant at the 0.01 level (2-tailed).

To avoid repetition, I present only the spatial autocorrelations analysis for the Gini coefficient, because all human capital inequality indices are highly correlated with one another. The Moran's I statistic for the rook first order contiguity spatial weights schemes over the period 1995–2000 shows a positive spatial autocorrelation (Table 4.8). The space-time statistics are also high. For instance, the Moran's I statistic between an example of within-region inequality in 2000 and inequality in neighbouring regions in 1998 is 0.7280, which depicts the space-time correlation in 1998, while the univariate Moran's I statistic for 2000 is 0.7150. Constructing the 3-nearest neighbours spatial

[68] The ratio of skewness to standard error is 0.31 for the Gini coefficient, 2.02 for the Theil index, 2.36 for the squared coefficient of variation, 0.32 for the relative mean deviation index and 1.88 for the Atkinson index. In view of the sensitivity of the Atkinson index to income, once again, this index should become more sensitive to 'transfers' among people who completed their highest formal studies when they were young and less sensitive to 'transfers' among people who completed their studies when they were older. Additionally, at higher values the sensitivity parameters of the Atkinson index (i.e. $\varepsilon = 1$ and $\varepsilon = 2$) fit better to the normal distribution because the ratio of skewness to standard error is lower (i.e., AA100=1.72 and AA200=1.42, respectively).

weights schemes, the univariate and bivariate Moran's I statistic (the spatial autocorrelation and the space-time correlation, respectively) are high. Finally, the Moran's I statistics based on the distance band are much lower than the former schemes.

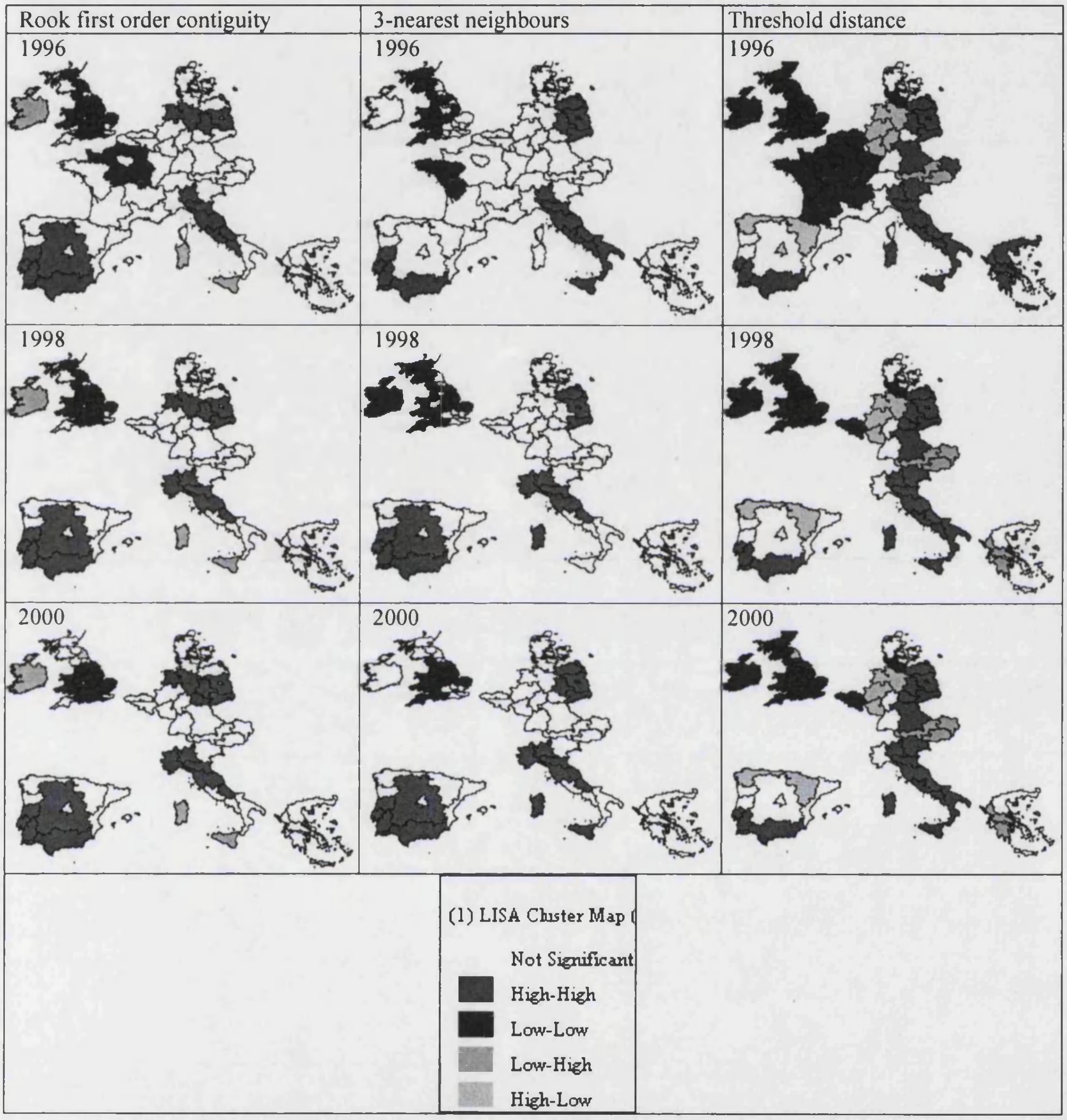
Table 4.8: Moran's I for the Gini Coefficient on Age at which the Highest Education Level was Completed (AGINI)

		Excluded SE LU (E[I]=-0.0109)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.7366	-0.0071	0.0761	9.7727	0.7902	-0.0091	0.0797	10.0289	0.3872	-0.0115	0.0233	17.1116
	1996	0.7385	-0.0097	0.0741	10.0972	0.7913	-0.0111	0.0817	9.8213	0.3845	-0.0136	0.0214	18.6028
	1997	0.7319	-0.0079	0.0777	9.5212	0.7827	-0.0091	0.0813	9.7392	0.3807	-0.0102	0.0236	16.5636
	1998												
	1999												
	2000												
Space-time correlation	1998												
	2000												
		Excluded SE LU FR (E[I]=-0.0119)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1995	0.7743	-0.0083	0.0832	9.4063	0.8516	-0.0117	0.0800	10.7913	0.4541	-0.0115	0.0269	17.3086
	1996	0.7774	-0.0121	0.0834	9.4664	0.8532	-0.0101	0.0801	10.7778	0.4519	-0.0132	0.0263	17.6844
	1997	0.7701	-0.0115	0.0805	9.7093	0.8436	-0.0161	0.0784	10.9656	0.4477	-0.0103	0.0266	17.2180
	1998	0.7557	-0.0154	0.0813	9.4846	0.8440	-0.0087	0.0799	10.6721	0.4098	-0.0132	0.0255	16.5882
	1999	0.7565	-0.0130	0.0820	9.3841	0.8393	-0.0099	0.0784	10.8316	0.4070	-0.0106	0.0261	16.0000
	2000	0.7150	-0.0108	0.0807	8.9938	0.8026	-0.0110	0.0772	10.5389	0.3527	-0.0121	0.0263	13.8707
Space-time correlation	1998	0.7696	-0.0109	0.0783	9.9681	0.8527	-0.0102	0.0795	10.8541	0.4184	-0.0113	0.0256	16.7852
	2000	0.7280	-0.0042	0.0814	8.9951	0.8089	-0.0143	0.0769	10.7048	0.3766	-0.0107	0.0256	15.1289

Note: All statistics are significant at p=0.001; E[I]: theoretical mean; Mean: observed mean.

Figure 4.15 displays the cluster maps for inequality in age at which the highest education level was completed in 1996, 1998 and 2000, at three weights schemes. They confirm the local variation in the spatial autocorrelation. Inequality in human capital is concentrated in particular areas of Europe. The regions with relatively high levels of educational inequality (respectively low) are more often located close to other regions with a relatively high degree educational inequality (respectively high) rather than their location being purely random. Different trends in inequality distribution exist over the EU space. The weights schemes of the first order contiguity and the 3-nearest neighbours show that clusters of regions with high educational inequality are found in central and northern Italy (Nord Ovest, Lombardia, Emilia-Romagna and Centro), in southern Portugal (Lisboa, Alentejo and Algavre) and in eastern Germany (Brandenburg, Mecklenburg-Vorpommern and Sachsen). Additionally, the southern Portugal cluster extends further for the distance band schemes to include southern Spanish regions. In contrast, most British regions are clusters with low human capital inequality. The distance band weights schemes create larger clusters than the previous schemes. Furthermore, Noroeste, Noreste, Niedersachsen, Nordrhein-Westfalen, Rheinland-Pfalz and Saarland are spatial outliers over the period 1996–2000.

Figure 4.15: Cluster Map for the Gini Coefficient on Age at which the Highest Education Level was Completed (AGINI) in 1996, 1998 and 2000



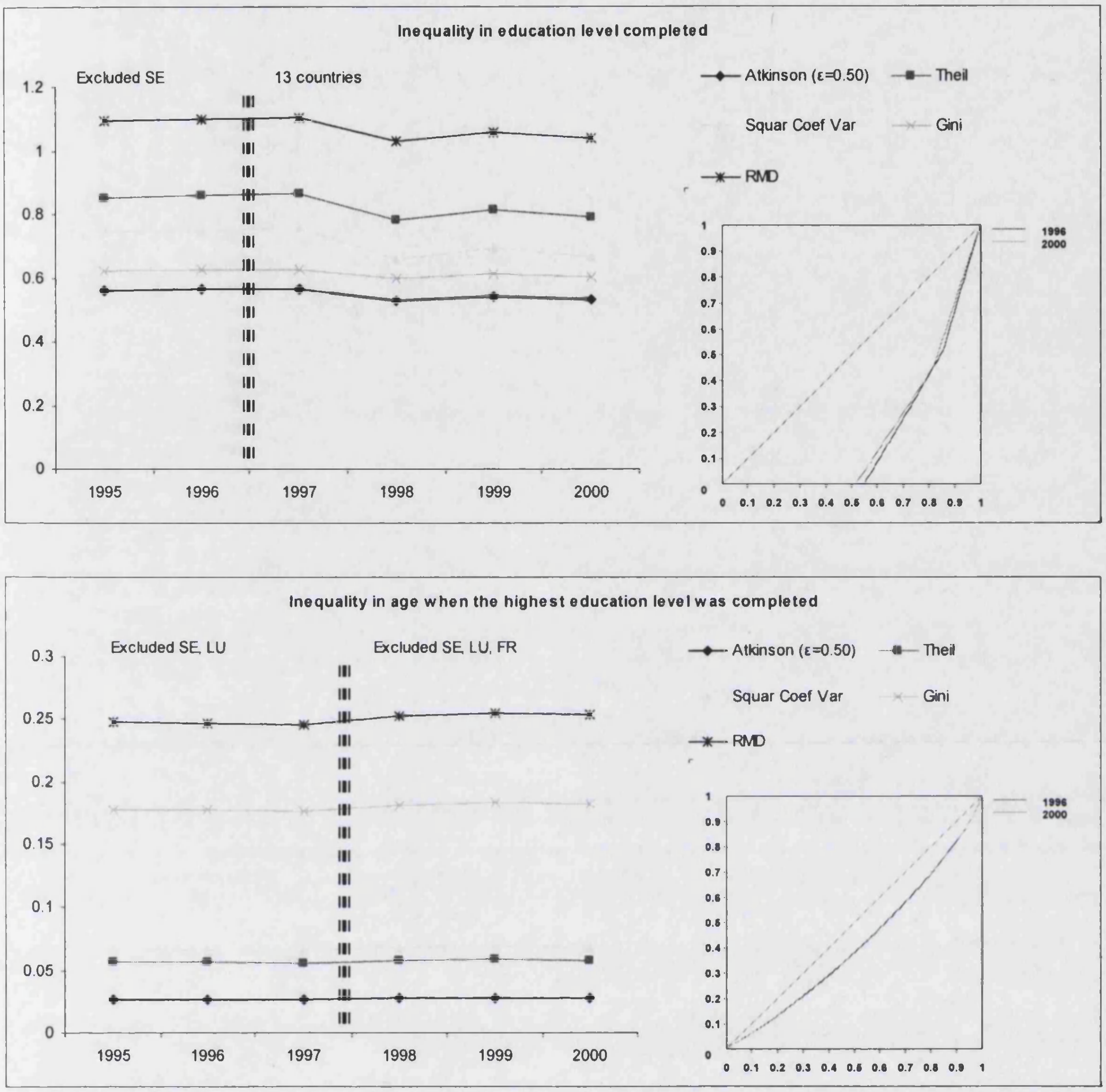
Considering the inequality in the age at which the highest education level was completed, the maps and the boxplots reveal one key source of spatial heterogeneity, which is the degree of urbanisation. This seems to be negatively correlated with educational inequality. The figures show an increase in the homogeneity within urban centres and within rural areas. Spatial autocorrelation seems to favour the diffusion of human capital activities from one urban centre to another or from the inner to the outer city, rather than from the urban centre to the periphery. Nevertheless, the distance between these groups remained the same, highlighting the stagnation of the polarisation or stratification process, on the one hand, and the persistence of educational inequality, on the other. Hence the existence of autocorrelation, heteroskedasticity and persistence highlights the need for space-time analysis of educational inequality.

4.3.4 Within-region Educational Inequality as a Component of the Educational Inequality in Europe

In this subsection, educational inequality within regions is considered as a component of European educational inequality, through the use of the two-stage nested Theil decomposition method to explore individual-level human capital data (both for the highest education level completed and for the age at which the highest education level was completed) for the EU.

Educational inequality is measured using the relative mean deviation index, the Theil index, the squared coefficient of variation, the Gini coefficient and the Atkinson index. The short evolution of both proxies for educational inequality in Europe is presented in Figure 4.16. It also illustrates the Lorenz curve, which shows that educational inequality was higher in 1996 than in 2000.

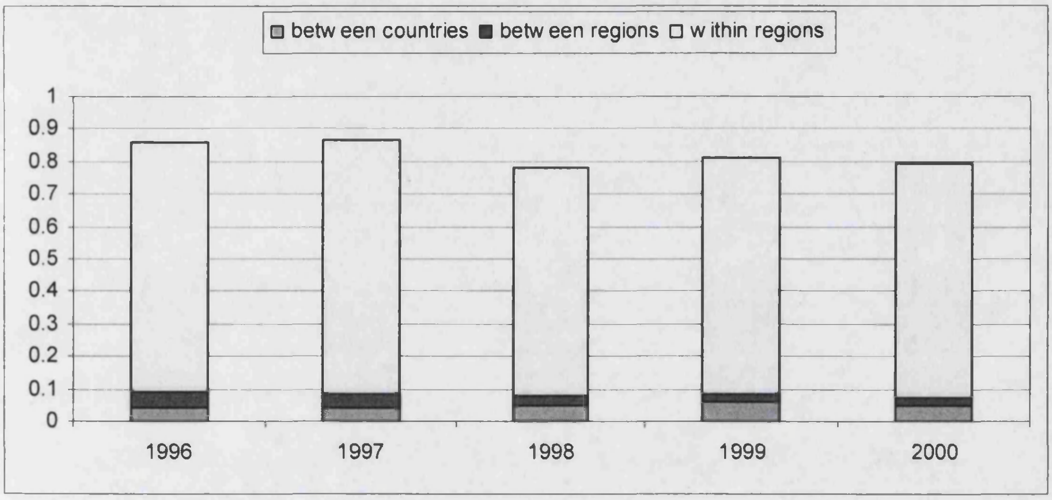
Figure 4.16: The Evolution of European Human Capital Inequality



First, with regard to the highest education level completed, inequality in Europe fell considerably from 1997 to 1998. Second, with regard to the age at which the highest education level was completed, the educational inequality in Europe remained the same not only from 1995 to 1997, but also from 1998 to 2000.

Figure 4.17: Three-level Human Capital Decomposition by Theil Index for the EU from 1996 to 2000

Inequality in Education Level Completed



Inequality in Age at which the Highest Education Level was Completed

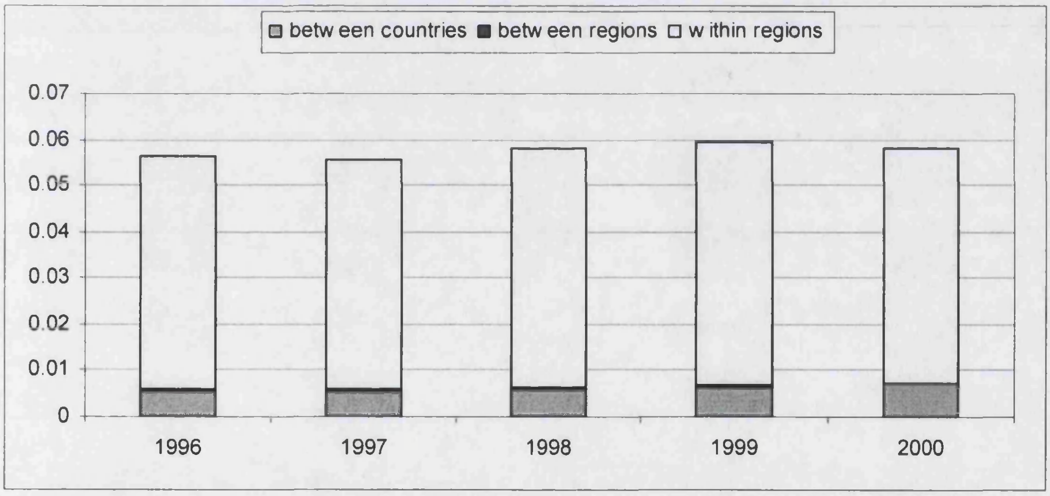


Figure 4.17 shows the results from the application of the two-stage nested Theil decomposition method for inequality in education level completed and for inequality in the age at which the highest education level was completed. The contribution of the three components — inequality between-countries, between-regions and within-regions — to overall human capital inequality in Europe was pretty much the same between 1996 and 2000. In 1996, for instance, 89.64 per cent of the overall inequality in education level completed and 89.71 per cent of the overall inequality in age at which the highest education level was completed was due to the within-region component. The between-region and between-country components of inequality in the education level completed accounted for 5.34 per cent and 5.02 per cent, respectively; and those components of inequality in the age a which the highest grade was completed comprised

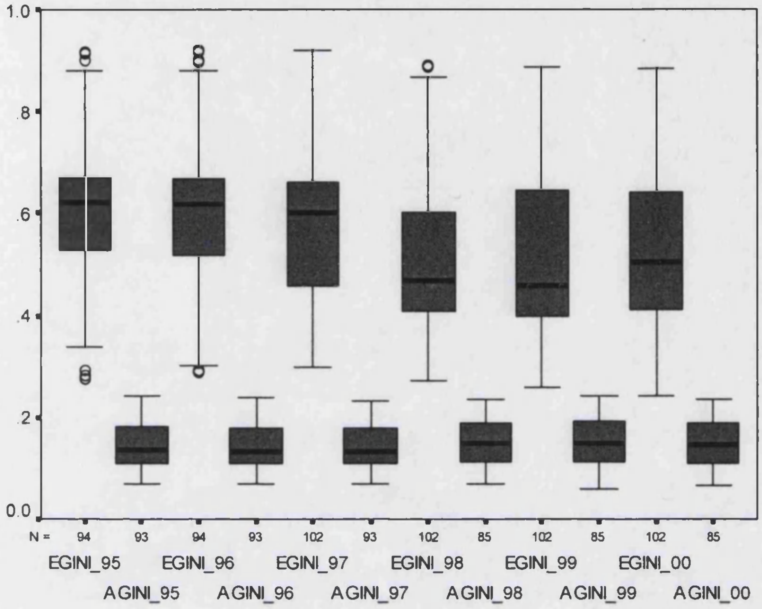
0.65 per cent and 9.64 per cent. The within-region component of educational inequality constitutes the major portion of the educational inequality in Europe. Furthermore, the between-region component of inequality in the age at which the highest education level was reached represents a very minor portion of the educational inequality in Europe. It is likely to involve country-specific factors, such as national educational policies and guidelines, which have a common effect on all regions within national borders. The inequalities based on individual human capital data are much higher than the inequalities based on aggregated data (i.e. national educational inequality). This figure provides arguments for an influence of national factors as national policies or legislation. Country-specific factors are likely to have a common effect on all regions within national borders. Once again, policy-makers should pay more attention to the within-region educational inequalities than to the between-region and between-country inequalities, because the within-region inequalities are far more prominent than the other components. This may lead to the formulation of better welfare policies.

4.3.5 The Relationship between the Two Proxies for Educational Inequality

The relationship between inequality in the education level completed and inequality in the age at which the highest education level was completed is investigated by the comparison of their boxplots, the Pearson correlation index and the bivariate Moran's I statistic.

First, on a comparison of the univariate boxplots of proxies for educational inequality (Figure 4.18), it is found that the distributions of both proxies are quite compact. However, the difference between the two whiskers of distributions for inequality in the education level completed is approximately triple that of inequality in age. Furthermore, the minimum value of the distribution for inequality in the education level completed is the maximum one for the other proxy for educational inequality.

Figure 4.18: Boxplot for the Gini Coefficient on Education Level Completed (EGINI) and Gini Coefficient on Age at which the Highest Education Level was Completed (AGINI)



Note: extreme cases and outliers are sorted in descending order: EGINI: PT3, PT2, PT15 and PT14 (upper end); DE4, DEE, DED and DEG (lower end) in 1995; PT2, PT3, PT12, PT14, PT15 and PT11 (upper end); DED and DEG (lower end) in 1996; PT14 and PT12 (upper end) in 1998 (see Appendix A1.1).

Second, measuring the Pearson correlation index, a positive linear correlation is noted for 1998, 1999 and 2000 (Table 4.9).

Table 4.9: Pearson Correlation between Two Proxies for the Gini Coefficient on Education

	1995	1996	1997	1998	1999	2000
EGINI-AGINI	0.053 (0.627) 85 0.069 (0.510) 93	0.062 (0.576) 85 0.073 (0.486) 93	0.090 (0.412) 85 0.104 (0.319) 93	0.456 (0.000)** 85	0.443 (0.000)** 85	0.261 (0.016)* 85

Note: ** correlation is significant at the 0.01 level (2-tailed); * correlation is significant at the 0.05 level (2-tailed).

Third, the correlation between the Gini coefficient on the education level completed in a region and the Gini coefficient on the age at which the highest education level was completed in neighbouring regions, and vice versa, are explored. In 1996, for instance, the bivariate Moran's I statistic is not significant either. Conversely, in 1998, for which the Pearson correlation has the highest value, the bivariate Moran's I statistic between inequality in education level completed in a region and inequality in age in neighbouring regions is 0.3712, while that between inequality in age in one region and inequality in education level completed in neighbouring regions is 0.3843 for first order contiguity spatial weights schemes, 0.4663 and 0.4323, respectively, for 3-nearest neighbours weights schemes, and 0.2742 and 0.2797, respectively, for threshold distance band weights schemes. These statistics are significant at the 0.001 level.

4.4 Correlation between Educational Attainment and Educational Inequality

In this subsection, the correlation between educational attainment and educational inequality is explored, considering both proxies.

Table 4.10 illustrates the Pearson correlations between the average educational attainment and inequality in the education level completed. The relationship is negative and statistically significant at the 0.01 level. The higher the educational attainment, the lower the educational inequality, and vice versa. Education seems to be one of the most powerful instruments known for reducing educational inequality. An increase in opportunities to acquire higher education is likely to reduce the educational inequality, as more people are able to improve their socioeconomic circumstances. Educational expansion seems to offer more educational opportunities and numerous favourable chances to both advantaged and disadvantaged groups.

Table 4.10: Pearson Correlation between Average Education Level Completed (EMN) and Inequality in Education Level Completed

	1995	1996	1997	1998	1999	2000
EGINI	-0.899 (0.000)** 94	-0.869 (0.000)** 94	-0.892 (0.000)** 94 -0.901 (0.000)** 102	-0.900 (0.000)** 94 -0.9 (0.000)** 102	-0.902 (0.000)** 94 -0.902 (0.000)** 102	-0.880 (0.000)** 94 -0.882 (0.000)** 102
EGE1	-0.898 (0.000)** 94	-0.876 (0.000)** 94	-0.890 (0.000)** 94 -0.898 (0.000)** 102	-0.853 (0.000)** 94 -0.854 (0.000)** 102	-0.866 (0.000)** 94 -0.866 (0.000)** 102	-0.877 (0.000)** 94 -0.879 (0.000)** 102
EGE2	-0.785 (0.000)** 94	-0.771 (0.000)** 94	-0.781 (0.000)** 94 -0.784 (0.000)** 102	-0.766 (0.000)** 94 -0.769 (0.000)** 102	-0.791 (0.000)** 94 -0.794 (0.000)** 102	-0.811 (0.000)** 94 -0.815 (0.000)** 102
ERMD	-0.904 (0.000)** 94	-0.876 (0.000)** 94	-0.894 (0.000)** 94 -0.902 (0.000)** 102	-0.856 (0.000)** 94 -0.849 (0.000)** 102	-0.858 (0.000)** 94 -0.852 (0.000)** 102	-0.855 (0.000)** 94 -0.853 (0.000)** 102
EA050	-0.907 (0.000)** 94	-0.879 (0.000)** 94	-0.896 (0.000)** 94 -0.905 (0.000)** 102	-0.869 (0.000)** 94 -0.865 (0.000)** 102	-0.871 (0.000)** 94 -0.868 (0.000)** 102	-0.860 (0.000)** 94 -0.862 (0.000)** 102

Note: ** correlation is significant at the 0.01 level (2-tailed).

Table 4.11 shows the Pearson correlations between average educational attainment and inequality in the age at which the highest education level was completed. This relationship is positive but not statistically significant for the squared coefficient of variation over the period 1995–2000 and for the Theil and the Atkinson indices for the period between 1995 and 1997. This is probably because occupations that require high levels of investment in human capital are beyond the reach of most poor people, who choose instead to work for others (Banerjee and Newman, 1991, 1993). Another possible explanation is that the poor require relatively higher returns in order to increase their expenditure on education, so they invest smaller shares of their income in education than the rich do (Ceroni, 2001). Those measures that encompass experience, learning by doing and on-the-job training may positively affect educational inequality, such opportunities are likely to be offered to the already advantaged groups. For instance, people with more work experience may be more informed and make better choices than those with little experience.

Table 4.11: Pearson Correlation between the Average Age at which the Highest Education Level was Completed (AMN) and Inequality in the Age at which the Highest Education Level was Completed

	1995	1996	1997	1998	1999	2000
AGINI	0.240 (0.027)* 85 0.267 (0.010)** 93	0.238 (0.028)* 85 0.263 (0.011)* 93	0.251 (0.020)* 85 0.275 (0.008)** 93	0.360 (0.001)** 85	0.356 (0.001)** 85	0.351 (0.001)** 85
AGE1	0.125 (0.254) 85 0.165 (0.114) 93	0.130 (0.236) 85 0.166 (0.112) 93	0.140 (0.200) 85 0.174 (0.095) 93	0.265 (0.014)* 85	0.257 (0.017)* 85	0.243 (0.025)* 85
AGE2	0.064 (0.559) 85 0.110 (0.294) 93	0.071 (0.517) 85 0.113 (0.283) 93	0.077 (0.481) 85 0.117 (0.265) 93	0.207 (0.058) 85	0.210 (0.053) 85	0.177 (0.105) 85
ARMD	0.261 (0.016)* 85 0.288 (0.005)** 93	0.265 (0.014)* 85 0.290 (0.005)** 93	0.282 (0.009)** 85 0.305 (0.003)** 93	0.389 (0.000)** 85	0.375 (0.000)** 85	0.364 (0.001)** 85
AA050	0.147 (0.179) 85 0.184 (0.077) 93	0.151 (0.168) 85 0.185 (0.077) 93	0.163 (0.136) 85 0.195 (0.062) 93	0.285 (0.008)** 85	0.273 (0.012)* 85	0.268 (0.013)* 85

Note: ** correlation is significant at the 0.01 level (2-tailed); * correlation is significant at the 0.05 level (2-tailed).

4.5 Conclusion

The European regions differ with regard to the average educational attainment and inequality in human capital. The geographical distribution of educational attainment and inequality is not uniform. It is characterised by significant positive global spatial autocorrelation and space-time correlation. The evolution of education within a region is closely related to its evolution in neighbouring regions (denoting spatial autocorrelation). The spatial evolution of education affects the dynamic evolution of human capital through geographical distances and proximity (showing space-time correlation). For instance, a region surrounded by highly-educated economies can achieve a higher educational stock. The reverse is also true. The use of Moran's I statistics leads to the same results for the sign (positive) and significance of global spatial dependence, highlighting the robustness of the results with regard to the choice of the spatial weights matrix. Since labour is a mobile production factor, public infrastructure investments in one region can draw production away from other regions or provide access to adjacent regions that were not previously accessible (Lall and Yilmaz, 2001). Regional variations in educational attainment and inequality are likely to reveal regional variations in the average attainment and inequality in skills, efforts, opportunities, knowledge and aspiration, on the one hand; and national institutional differences, on the other. The application of the global and local spatial association tests leads to the detection of educational patterns in the territory of the EU, which have not changed dramatically throughout the whole period of study, denoting a persistence in patterns of of educational attainment and inequality in specific regions. Human capital is an important factor in shaping regional interactions. Regional disparities in education are influenced by region- and nation-specific characteristics and the availability of highly-educated people in neighbouring regions.

The ESDA on education emphasises some kind of spatial heterogeneity hidden within the spatial autocorrelation pattern. The spatial effects perform differently according to two regimes: the urbanisation pattern and the European north-south divide. There are systematic differences between urban and rural European regions and between northern and southern European regions. Because of the spatial interactions between regions, geographical location (urban or rural and north or south) is important in accounting for the human capital performance of regions. Regions are geographically correlated due to certain processes, which connect different areas, such educational diffusion and the existence of national institutions. Vaya et al. (2004: 433) point out that externalities spill over the barriers of regional economies, in a process that resembles the cross economy interactions outlined in Lucas (1988; 1993). They also emphasise that there are spatial limits to the spread of externalities and that the diffusion of skills and knowledge will always be easier within groups of closely related economies ('clubs'). Economies within a group (i.e. the group of northern European countries) interact more with one another than with those outside the group. The diffusion of human capital seems to be stronger between regions of the same economy than the diffusion between national economies. The analysis shows that educational policies should account for the spillover effects with adjoining regions. The prevalence of interregional educational externalities may have created a 'human capital poverty trap', based on geographical location.

Finally, the within-region component of educational inequality constitutes the major portion of European educational inequality, while the between-region component represents the minor portion.

5 Chapter Five. The Income-Education Relationship and Regional Economic Growth

5.1 Introduction

The contribution of this chapter is to analyse the relationship between income and educational distributions through the examination of the parametric models of lognormal and gamma distributions, cross-tabulation analysis and the comparison of the within-region income and educational inequalities.[69] This chapter also explores the spatial autocorrelation and spatial heterogeneity of regional economic growth. The core methodology used is descriptive analysis.

This chapter consists of two sections and proceeds as follows. Section 5.2 examines the relationship between income and educational distribution. It firstly tests whether the income and educational distributions in Europe follow the lognormal and gamma distributions. Then, it examines the evolution of the income-education relationship using cross-tabulation analysis. Finally, it looks at the within-region inequalities as components of the European inequalities. Section 5.3 displays ESDA on regional economic growth. The last section offers some conclusions.

5.2 The Relationship between Income and Educational Distribution

5.2.1 Lognormal and Gamma distributions

Both lognormal and gamma distributions have been used in the study of income distribution (i.e. Aitchison and Brown, 1957; Salem and Mount, 1974). In this subsection, the income and educational distributions for Europe are tested for whether they follow the lognormal and gamma distributions. The hypothesis is that both distributions follow the lognormal and gamma ones, because, in accordance with the theoretical background, income and education are positively correlated.

(1) The general form of the lognormal density function is

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[69] This chapter deals only with income distribution for the population as a whole, due to the minor differences between distributions for the population as a whole and for normally working people.

$$f(x;\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma^2}(\ln(x)-\mu)^2\right],\ 0<x<\infty,\sigma>0,$$

Where the estimated parameters are μ and σ (Gamulka, 2001).

(2) The gamma density function is

$$f(x;\alpha,\sigma)=\frac{1}{\sigma\Gamma(\alpha)}\left(\frac{x}{\sigma}\right)^{\alpha-1}\exp\left(-\left(\frac{x}{\sigma}\right)\right),\ x>0,\sigma>0,\alpha>0,$$

where the estimated parameters are α and σ (Gamulka, 2001).

The analysis performed here provides the Maximum Likelihood (ML) and the optimal B-robust estimator (OBRE)[70] testing ground for hypothesis. The OBRE estimation of these parametric models is less efficient than the ML estimation, but it is also less sensitive to data errors (Gamulka, 2001). In practical terms, more weight is given to the bulk of the data, less to the tails (Gamulka, 2001). For OBRE, the 'robustness constant' c is equal to 3.[71] Table 5.1 displays the estimated parameters and the standard errors of the lognormal and gamma distributions over the period 1995–2000.

The findings show that the lognormal distribution fits that of the individual income data much better than the gamma distribution, because the standard error on the parameter σ for gamma distribution is very high. Besides, the lognormal curve is the better approximation for the lower range of incomes (Aitchison and Brown, 1957). Nevertheless, both proxies for educational distributions fit individual data. The estimated parameters are likely to indicate a correlation between income and human capital, but this correlation seems not to be perfect, since their parameters are not close to one another.

Table 5.1: Lognormal and Gamma Distributions

	Lognormal distribution		Gamma distribution	
	μ	σ	a	σ
Distribution of income for the whole of the population	7.6885 (0.0040) 8.8204 (0.0022)	3.3124 (0.0028) 1.7620 (0.0016)	0.3166 (0.0004) □	33292.4 (84.2211) □
Distribution of education level completed	0.4024 (0.0005) 0.4024	0.4386 (0.0003) 0.4634	5.2278 (0.0081) 4.6878	0.3158 (0.0005) 0.3546

70 See Hampel et al. (1986).

71 The bigger the value of c, the less robust and more efficient OBRE is; in the limiting case $c=\infty$, OBRE becomes identical with ML (Gamulka, 2001).

	(0.0005)	(0.0004)	(0.0077)	(0.0006)
Distribution of age at which the highest education level was completed	2.8358 (0.0004) *2.8120* *(0.0004)*	0.3075 (0.0003) *0.2880* *(0.0003)*	9.8980 (0.0183) *12.4156* *(0.0248)*	1.8129 (0.0034) *1.3862* *(0.0028)*

Note: The standard errors are in parenthesis. The OBRE estimations are in italics (therelative precision is 0.001 and the max iteration is 20).
□: The estimated α = 0.3166 is out of the range covered by the algorithm.

5.2.2 The Income-Education Relationship: A Cross-tabulation Analysis

According to the literature, income and human capital are expected to be positively correlated. Figure 5.1 shows the relationship between the individual's total net personal income and his/her educational attainment. The higher the level of education completed by the individual, the higher his/her total income. One should bear in mind that the income-education relationship is lagged. An individual's educational level makes a difference to their income. First of all, people who hold a recognised qualification at the tertiary education level have a higher income in general than people who have completed the second stage of secondary level education, who, in turn, have a higher income in general than people who have completed less than the second stage of secondary level education. Secondly, similar results are demonstrated when I consider the age of the respondents on completion of their highest education level. A categorical variable with six educational categories (age bands) has been created. The findings show that the higher the age-related educational categories, the higher the income per capita, for all but the last category. To sum up, the cross-tabulation analysis illustrates the positive correlation between income and education.

(1) *From education to income*: The findings are likely to demonstrate that an individual's success in the educational arena seems to be the predominant factor influencing his/her eventual occupational attainment and rewards, and thus his/her income levels (Ainsworth and Roscigno, 2005). People generally require higher education in order to get better paid jobs. Better-educated people are also more productive, because they are socialised in ways to increase their productivity and to improve their economic standing by making effective social networks. People who remain in school, are likely to acquire some specific traits that increase their productivity. Additionally, they are likely to have a higher level of aspiration and, therefore, to put more effort into their career in order to secure high-wage jobs (Hansen, 2001). Education, therefore, seems to be central to occupations and incomes. Those who are otherwise able, but lack appropriate credentials are likely to be excluded from high-wage jobs. Once people have obtained the necessary credentials, they are more likely to

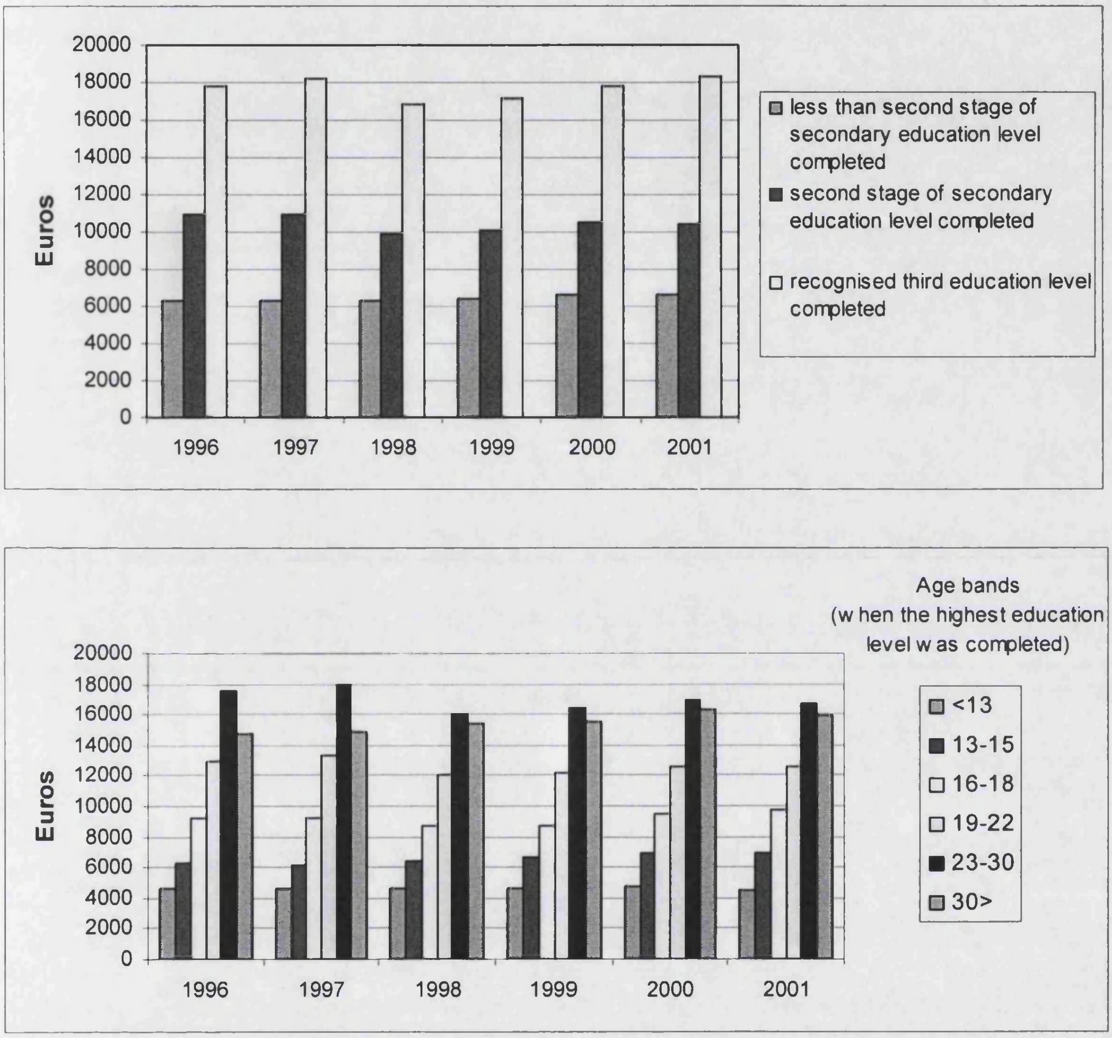
secure a well-paid job. Education enables individuals to improve their economic circumstances, because it offers credentials that signal underlying abilities, preferences and privileges (Hannum and Buchmann, 2005). Education usually offers plenty of economic opportunities to both advantaged and disadvantaged groups. The potential of education for reducing income inequality seems to be associated with abilities, choices, preferences and the level of aspiration, because these factors enable individuals to improve their economic status. One should also keep in mind that individuals differ not only with regard to their potential skills and preferences, but also with regard to their inherited wealth, which crucially determines whether they can afford to invest in human capital. Income is, therefore, likely to be an indirect source of one's academic credentials. Each person wants to maximise his/her economic welfare by investing an appropriate amount in human capital (Becker and Chiswick, 1966). Consequently, income seems to be a function of an individual's ability, education and other legitimate training.

(2) *From income to education*: An individual's income level seems to be a crucial factor in his/her educational choices and opportunities. Although the European capital market is not so perfect that anyone may borrow for their education against their expected future earnings, the imperfect information about individual abilities and the imperfect enforcement of educational loans does not appear to greatly restrict the option of borrowing for education, because most people rely heavily on their own sources of finance to invest in education, while at the same time the cost of human capital is relatively low (Alesina and Perotti, 1994). Rich people often inherit a large initial sum and do not need to borrow in order to gain better access to education. Nevertheless, a few European citizens (or families) face credit constraints that prevent them from continuing to a profitable level education level, although primary and secondary education is compulsory and the tuition fees for tertiary education are relatively low. One should also bear in mind that human capital may serve as collateral in some European countries (i.e. the United Kingdom), although it is not possible to expropriate. Another explanation for the income-education relationship is that the process of development alters the demand for and supply of different types of labour, the returns to and allocations of occupations and, hence, the educational choices (Banerjee and Newman, 1993).

Consequently, education in Europe is correlated with economic status, measured in terms of income, because it reflects an individual's lifetime economic opportunities.

Education exerts an influence on the demand for and supply of skilled labour, and hence on the relative wages (Tinbergen, 1975). The differences in income across individuals may reflect the differences in educational opportunities (Johnson 2002).

Figure 5.1: Income Per Capita (t-1) and Educational Categories (t) from 1996 to 2001



5.2.3 Comparing the Within-region Income Inequality with the Within-region Educational Inequality as Components of European Inequality

Figure 5.2 illustrates the percentage of the within-region, between-region (but within country) and between-country inequality components of European income and educational inequality. The within-region income and educational inequality components represent the major portion of European inequality. The inequalities that are based on the average level of a distribution (the between-region and between-country components) are much lower than inequalities that are measured at the individual level (the within-region component). Thus, relatively high inequalities exist among the individuals within each European region.

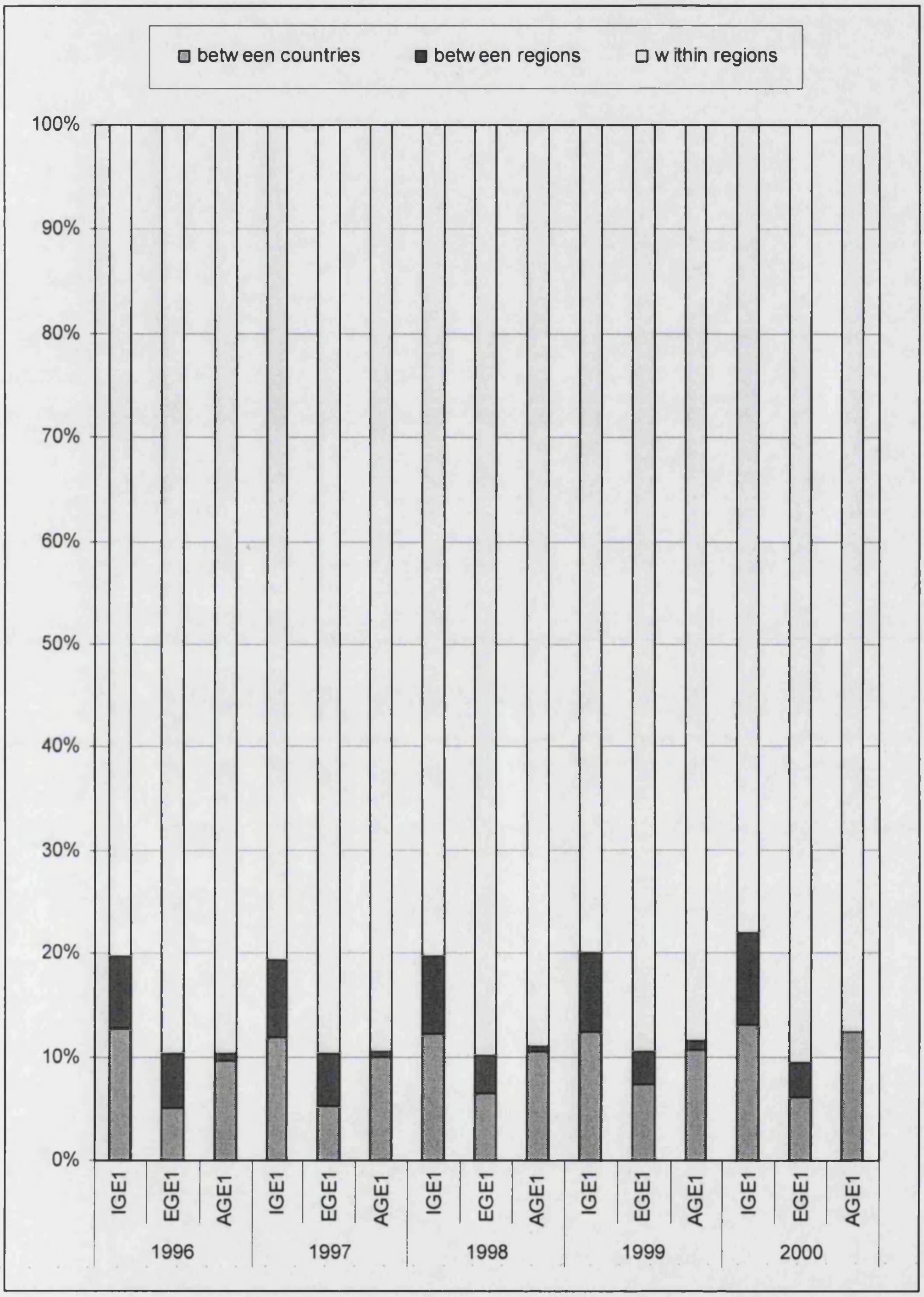
Comparing inequalities based on the average level of a distribution, the findings indicate that the between-country component accounts for a larger portion of the overall inequlity than the between-region component. This most probably is an indication that national policies (i.e. tax policies, trade reforms, educational policies) outweigh regional ones (i.e. public infrastructure policies).

The between-region component of income inequality is larger than the between-region component of inequality in education level completed, which in turn is larger than the between-region component of inequality in the age at which the highest level of education is completed. In 1998, for example, 7.54 per cent, 3.55 per cent and 0.52 per cent of the overall inequality was due to the between-region income, education level completed and age inequality components, respectively. This is most probably due to the fact that since national educational policies and guidelines have a common affect on all regions within national borders, they may halt any increase in the between-region income inequality, because people do not need to migrate for educational reasons (at least at primary and secondary education level). Thus, national educational policies seem to affect not only the spatial distribution of human capital, but also the spatial distribution of income.

The two-stage decomposition analysis indicates that the between-region component, which is the sum of the between-country and between-region components, is almost the same for both proxies for educational inequality, accounting for about ten per cent of the overall European inequality. Hence, there is a small disparity in educational inequality between the regions of the EU. This is possibly a reflection of the relatively low levels of interregional migration across different educational groups.

To sum up, policy-makers should place more emphasis on the within-region inequalities in income and education than on the between-region and between-country inequalities, because the former components account for the major portion of the EU inequality.

Figure 5.2: Three-level Income and Educational Decomposition by Theil Index for the EU from 1996 to 2000.



5.3 Regional Economic Growth

Regional economic growth ($GGR2I_{it}$) in region i and in year t is defined as $GGR2I_{it} = \frac{G_{it} - G_{i,t-2}}{G_{i,t-2}}$, where G_{it} denotes GDP per capita.

The first step of the descriptive analysis is to map the macroeconomic data in order to see whether regional economic growth is randomly distributed over the EU, or whether there are similarities between regions. Figure 5.3 shows the spatial distribution of economic growth in 1998, 2000 and 2002.

(1) In 1998: In the United Kingdom, Portugal and Spain, urban areas have a higher growth rate than peripheral and rural areas. The GDP per capita of rural areas diverges from the national average. In the United Kingdom, for instance, the regions around Greater London (Berkshire, Gloucestershire, Leicestershire and Bedfordshire) not only have the highest growth in Britain, but also belong to the list of the ten highest growth regions in Europe. This most probably reflects either the trickling down of economic development or, according to the NEG, the establishment of centrifugal forces in the growth process. The forces arising from product market and factor market competition such as the bidding up of local land and wage costs (Martin, 1999c: 68) outweigh those emanating from the home market and price index effect. Furthermore, closer integration in the EU combined with lower costs in London's neighbouring regions have tended to favour some diffusion of development. Cornwall, Lincolnshire, Cleveland, Humberside and Lancashire feature in the list of the ten lowest growth regions. In the United Kingdom, there is a north-south divide in the growth process. In Spain, the growth process is relatively buoyant in Comunidad de Madrid, but it is low in its neighbouring region (Centro). In this case, the centripetal forces may outweigh the centrifugal forces. The case of Madrid is appealing, because the large market and the high GDP per capita allow the producers to economise on the trade costs. The Spanish capital region's access to major markets is not impeded by large trade costs. These tend to reward its factors with higher wages and high economic growth.

(2) In 2000: Regional economic growth has changed slightly. The list of the ten highest growth regions includes the southern Swedish regions (Stockholm, Sydsverige and Västsverige). Growth seems to be more randomly distributed in 2000 than in 1998. Irish economic growth in 2000, as in 1998, is among the highest in the EU. It is described in the literature as the 'Irish economic model'. Many reasons have been suggested for Ireland's success such as the low corporation tax rate, the large multinational presence, the high proportion of the population of working age and increased participation in the

labour market especially by females, among others.[72] The combination of these factors can help explain the impressive Irish growth rates.

(3) In 2002: Regional economic growth has changed dramatically. There are striking disparities in growth performance between the central and the peripheral regions. The growth rate in Greece, Spain and Ireland, and in the less economically advanced British regions, is double the EU average. This most probably indicates some convergence in the EU. According to the European Commission (2004), convergence has been driven by the tighter European integration. In cohesion countries, the Structural Funds, the supply-side improvements and the shift into higher value-added sectors may all have played an important role in the convergence process. Growth seems to be randomly distributed in the British regions, while in Spain and in Greece it is evenly distributed. Finally, the process of catching up in three of the four Cohesion countries (Spain, Greece and Portugal) stems not only from growth in the relatively rich urban areas (particularly capital cities), but also from growth in the poorer regions.

Urbanisation seems to be a crucial factor in regional economic growth performance. The regions with the lowest growth rate are generally rural areas. According to the European Commission (2004), the urban areas are concentrated in or near the rich central part of the EU, reflecting the association of cities. In many peripheral parts, notably in Scotland, Ireland, Greece and Sweden, urban areas are relatively small and scattered, while rural areas predominate. The growth rate in urban areas is higher than that in rural areas, because towns and cities tend not only to be centres of prosperity, creativity, culture and innovation in the EU, but also communication hubs (European Commission, 2004). The major urban centres are also characterised by services. Companies, headquarters, research activity, education and centres of decision-making are concentrated in cities. Each city has a different degree of specialisation. Capital cities in Scandinavia, for example, are specialised in new technology. An analysis of the cooperation networks between towns and cities indicates the existence of a strong network of major 'metropoles' in the centre of Europe, including London, Paris Frankfurt, Amsterdam and Milan (European Commission, 2004: 28). Nevertheless, the main problems facing the EU, such as unemployment, are for the most part concentrated and accentuated in urban areas. For example, London has some of the most deprived areas in the EU. Urban areas can have a low-skilled workforce and can form islands of

[72] www.ersi.ie.

poverty within a prosperous region (European Commission, 2004). Rural areas contain a wealth of natural resources, habitats and strong cultural traditions and important tourist locations, on the one hand, yet on the other hand they are overdependent on resource-based activities, particularly in agriculture, which means that they are vulnerable to the restructuring and rationalisation of such sectors, and they also have low levels of output and income (European Commission, 2004). Finally, considering simultaneously the spatial distribution of GDP per capita, any divergence process within a country stems more from growth in relatively rich urban regions rather than from any activities in poorer regions.

Figure 5.3 also shows that latitude does not matter for growth. The levels of growth in northern and southern areas do not seem to have evolved differently.

Figure 5.3: Spatial Distribution of Regional Economic Growth (GGR2I) in 1998, 2000 and 2002

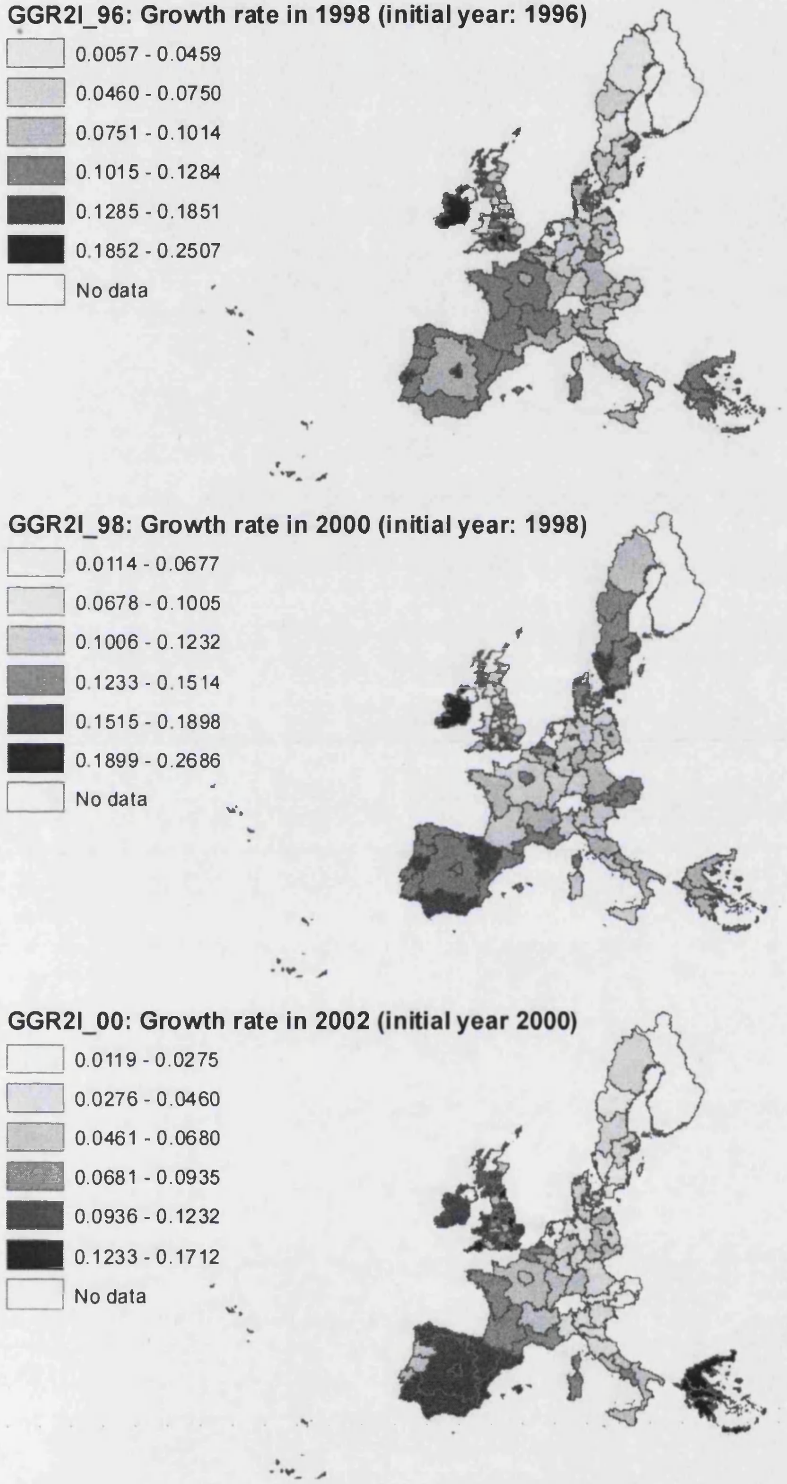
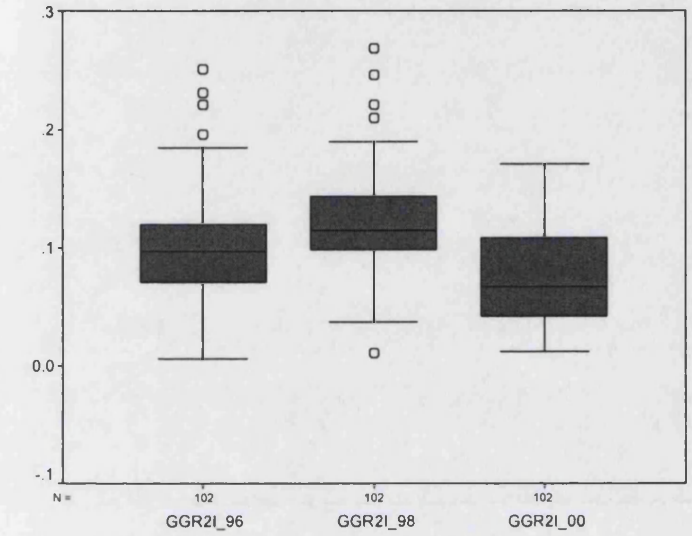


Figure 5.4 shows the boxplot for regional economic growth. In 1998, the peripheral regions of Ireland and Madeira, Berkshire and Luxemburg are outliers at the upper end of the distribution. In 2000, the outliers at the upper end of the distribution are the peripheral regions of Ireland, Madeira, Açores and Luxemburg, while the British region of Cumbria is an outlier at the lower end of the distribution. In 2002, the distribution of growth is the most compact. The growth rates of most European regions are between the

first and third quartile. Average regional growth in the EU increased between 1998 and 2000 by 0.229 per cent, while it decreased between 2000 and 2002 by 0.376, as a result of the short EU depression. The boxplot is likely to show some convergence in the EU.

Figure 5.4: Boxplot for Regional Economic Growth in 1998 (GGR2I_96), 2000 (GGR2I_98) and 2002 (GGR2I_00)



Note: extreme cases and outliers are sorted in descending order:
IE, LU, PT3, UK52 (upper end) in 1998; IE, LU, PT3, PT2 (lower end) and UK12 (upper end) in 2000 (see Appendix A1.1).

An examination of spatial effects highlights the possible importance of spatial interactions and geographical location for regional economic performance. The spatial autocorrelation for regional economic growth shows the relationship between similarity of growth and spatial proximity. This is displayed in Table 5.2. Due to the low Moran's I statistic for regional economic growth, it seems to be randomly distributed over space. This reinforces the view that latitude and institutions do not matter for growth.

Table 5.2: Moran's I for Regional Economic Growth (GGR2I)

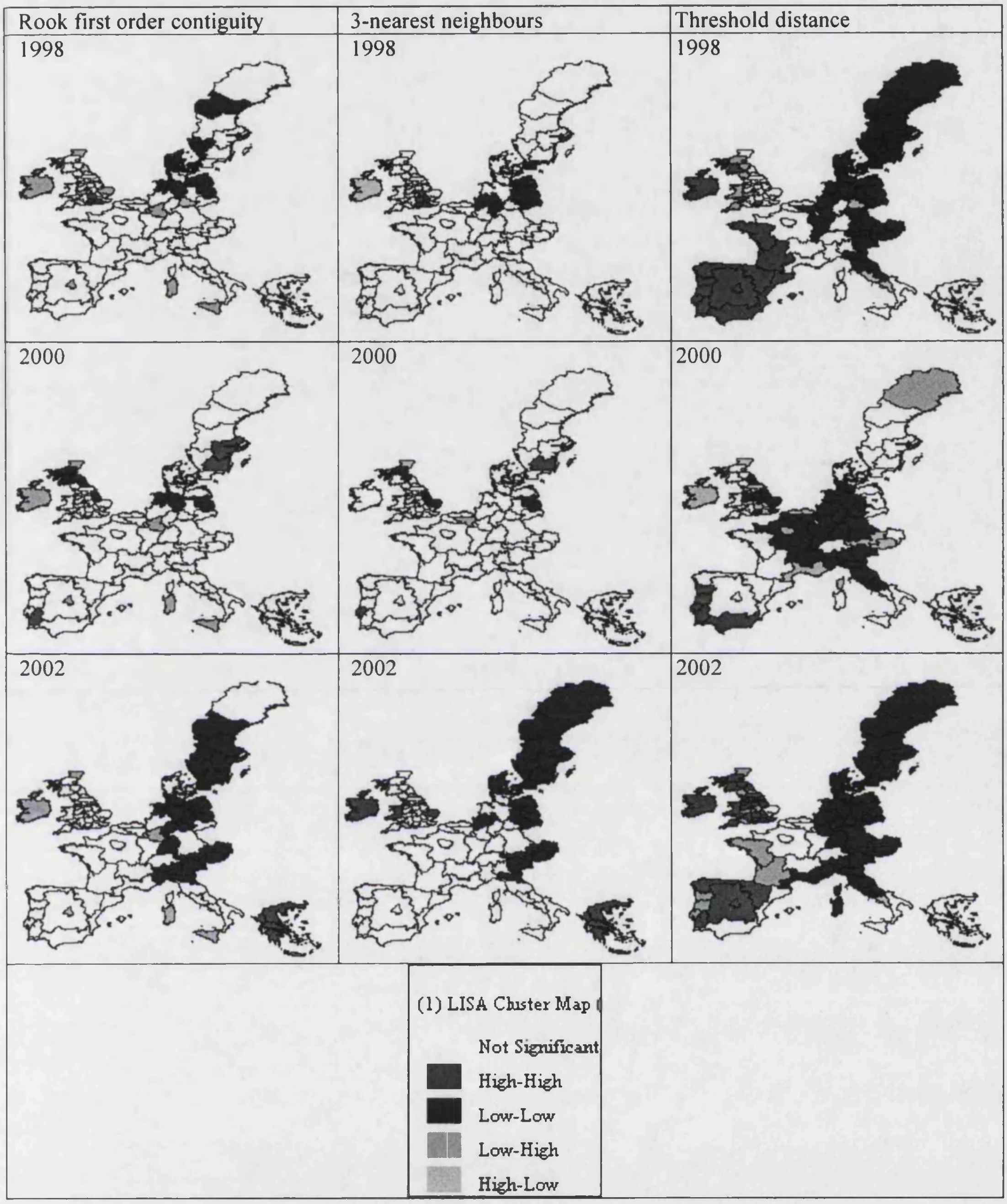
		13 countries (E[I]=-0.0099)											
		rook first order contiguity				3-nearest neighbours				threshold distance			
		Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value	Moran's I	Mean	Sd	Z-value
Spatial auto-correlation	1998	0.2571	-0.0164	0.0725	3.7724	0.3027	-0.0065	0.0741	4.1727	0.1494	-0.0108	0.0222	7.2162
	2000	0.2118	-0.0084	0.0748	2.9439	0.2166	-0.0097	0.0753	3.0053	0.1654	-0.0099	0.0234	7.4915
	2002	0.5941	-0.0097	0.0735	8.2150	0.6445	-0.0081	0.0730	8.9397	0.3191	-0.0101	0.0226	14.5664
Space-time correlation	2000	0.0829	-0.0063	0.0601	1.4842	0.1566	-0.0046	0.0585	2.7556	0.1273	-0.0050	0.0188	7.0372
	2002	0.0098	0.0000	0.0546	0.1795	0.0436	-0.0039	0.0566	0.8392	0.0622	-0.0009	0.0177	3.5650

Note: Space-time correlation in 2000 (rook first order contiguity), in 2002 (rook first order contiguity) and in 2002 (3-nearest neighbours) is not statistically significant; E[I]: theoretical mean; Mean: observed mean.

Figure 5.5 shows the cluster maps for regional economic growth in 1998, 2000 and 2002. They illustrate the local variations in spatial autocorrelation of regional growth.

According to the rook first order contiguity spatial weights matrix, the north-eastern European regions (the Swedish regions of Mellersta-Norrland and Västsverige, Denmark, and the German regions of Niedersachsen, Mecklenburg and Brandenburg) formed a cluster of low growth rate regions. In 2002, this cluster expanded southward to include Hessen, Baden-Württemberg, Austria and northern Italy. In 1998, clusters of high economic growth include the relatively advanced economic regions of the southern United Kingdom, indicating some divergence, while in 2000 and 2002 the rich clusters include the less economically advanced regions of Alentejo and Greece indicating some convergence in the EU. While the cluster maps of the first order contiguity schemes and the 3-nearest neighbours schemes are quite similar, the clusters created by the threshold distance weights schemes are more spread out. To conclude, spatial autocorrelation analysis indicates some convergence in the EU, because regional economic growth is higher in the less economically advanced regions than it is in the mostly prosperous ones. However, poor regions are still beset by weaknesses which limit competitiveness (European Commission, 2004).

Figure 5.5: Cluster Map for Regional Economic Growth (GGR2I) in 1998, 2000 and 2002



The above analysis suggests some forms of spatial heterogeneity. Urbanisation and country location seem to be underpinning factors behind regional economic growth. Although most regions are experiencing at least some convergence, their performance varies. Thus the pace at which the growth process occurs varies. Urbanised regions have performed differently than rural ones. Poor European regions seem to grow faster than rich ones. Although the income per capita of poorer regions is converging towards the EU average, they are not likely actually catch up due to differences in socioeconomic structures. Standard and augmented economic growth theories provide plenty of explanations of the convergence (Solow, 1956; Swan, 1956; Mankiw et al., 1992; Jones 1997, 1998). Concerning the heterogeneity across regions with regard to educational attainments, human capital investments, local government spending, urbanisation level and so on, European regions are likely to converge to different steady-states, because there are institutional and structural barriers to the transmission and absorption of technology across the European regions. Despite the narrowing of disparities, large differences remain. European regions seem to approach their own, but unique and globally stable, steady-state equilibrium.

5.4 Conclusion

The preliminary analysis shows that income distribution, educational distribution and regional economic growth evolve together.

First, this chapter has illustrated how income distribution is likely to replicate educational distribution. Both distributions follow the lognormal distribution, highlighting their high correlation. On the one hand, education enables individuals to improve their socioeconomic circumstances and, on the other, an individual's income level seems to be a crucial factor in his/her educational choices and opportunities. Regional variations in education are likely to show regional variations in skills, efforts, opportunities, social networks, knowledge, aspiration and national institutions, and thus regional variations in income, and vice versa. While both the within-region income inequality and the within-region educational inequality explain the major portion of the EU inequality, the between-region component of income inequality is larger than the between-region component of educational inequality.

Second, growth seems to depend on the initial level of growth (denoting the dynamic effects), as well as on a weighted average of initial regional growth in the neighbouring regions (denoting the spatial effects). Thus economic growth in each region depends not only on its own socioeconomic characteristics, but also on those of the regions that form the neighbourhood to which it belongs (Chua, 1993). Urbanisation and regional location seem to be underpinning factors behind regional economic growth, while latitude and institutions (the welfare stare, religion and family structure) are not. Growth rates vary from region to region in a way that suggests some convergence in the EU.

6 Chapter Six. The Determinants of Income and Educational Inequality

6.1 Introduction

The processes that create inequalities are not well understood, especially at a regional level. While the relationship between income and educational distribution has been an issue of considerable interest in the economic, sociological and political literature, there are few studies that developed linkages with different proxies for income and educational inequalities (i.e. Checchi, 2000; Heshmati, 2004; Justino et al., 2004). The analysis performed here represents an attempt to fill this gap. Hence, this chapter explores the determinants of income and educational inequality for the regions of the EU. The methodology is based on the estimation of both static and dynamic models. To evaluate the robustness of the results, a number of alternative specifications are tested.

The aim of this chapter is to analyse how microeconomic changes in human capital distribution affect income inequality and also how microeconomic changes in income distribution affect human capital inequality. Both distributions are measured in terms of their average and inequality. The contribution of this chapter is that it brings together knowledge from diverse disciplines and promotes interdisciplinary research on the determinants of income and educational inequalities. Although the general literature on inequalities is vast, the impact of income inequalities on educational inequalities, and vice versa, remains debated. This chapter also synthesises the available evidence from a range of economic, sociological and political studies. A mix of different theoretical models is needed to explain the potential patterns.

The structure of this chapter is as follows. Section 6.2 presents some theoretical considerations with regard to the impact of labour related variables, urbanisation, geography and institutions on inequalities. The selection of the determinants of inequalities draws on the theory, past studies and the ESDA on inequalities. The large, and sometimes persistent, gaps in inequalities reflect both differences in labour market performance and in regional specific characteristics such as location and institutions. This section also provides a brief descriptive analysis, mapping the above variables. The regression analysis of income inequality both for the population as a whole and for normally working people is presented in Section 6.3, while the estimations of various specification educational inequality models are presented in Section 6.4. Rooted in the theoretical literature review, Sections 6.3 and 6.4 are based on the critical assumption that both types of inequality are affected by the same determinants. Both sections provide a simple framework for understanding the differences in income and educational inequalities across EU regions and over time. The final section concludes with some policy recommendations.

6.2 The Determinants of Inequalities

This section introduces the theoretical background on the determinants of inequalities that are to be used in the regression analysis. I briefly discuss the pros and cons of the explanatory variables and offer a descriptive analysis of regional level disparities in the EU. The first subsection considers the labour-related time-variant variables, which are population ageing, access to work, unemployment and inactivity. The second subsection highlights the role of time-invariant variables such as urbanisation, latitude, the welfare state, religion and family structure.

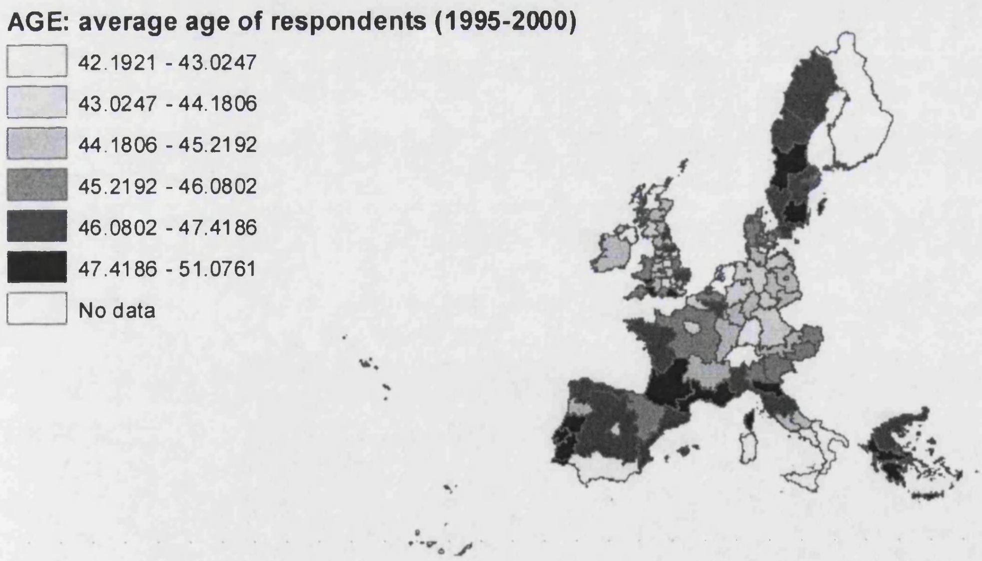
6.2.1 Labour Related Variables

6.2.1.1 Population Ageing

The impact of population ageing on inequality is ambiguous. On the one hand, an increase in the number of elderly and retired people, whose income is lower than the mature working age cohort, should lead to a rise in inequality (Estudillo, 1997). Additionally, as people get older, their lack of educational opportunities diversifies their income and human capital distribution (Motonishi, 2006). Their low chances of educational expansion at that time leave them with little opportunity to improve their economic circumstances. The elderly and the retired obtained the necessary credentials when they were young, the opportunities to acquire higher education do not usually increase as they get older. On the other hand, regions with a very young population will tend to have a lower rate of participation in the labour force, leading to high income and human capital inequalities. Young people in work will earn less in the labour market that rewards seniority, increasing inequality within a society (Higgins and Williamson, 1999). Finally, regions with a mature working age cohort tend to have lower inequality. These people do not face credit constraints that prevent them from increasing their level of education (Dur et al., 2004). The high education level of mature working age people may act as a determinant in improving their socioeconomic status and increasing their occupational outcomes.

Figure 6.1 shows the spatial distribution of population ageing, which is measured as the average age of respondents using ECHP survey data and is denoted by AGE. Kentriki Ellada, the Italian region of Emilia-Romagna, the French Sud-Ouest and Méditerranée, the Portuguese Centro, Lisboa, Alentejo and Algarve, the British Surrey and Dorset, and the Swedish Småland med öarna and Norra Mellansverige are the regions with the most elderly populations in the EU, while the Spanish Sur region, the Italian Campania, Sud, Sicilia and Sardegna and the British regions of Bedfordshire, Oxfordshire and Derbyshire have the youngest populations. Large urban areas, such as London, Paris and Madrid, have a lower average age than their respective national average, due to the increasing concentration of young adults in these regions. Young people move to core cities in search of better opportunities and a higher standard of living. The causes behind the cross-regional variation in European ageing are the variation in the cost of having children (i.e. these costs are greater in societies with a high female participation in the labour market), the variation in female employment status (i.e. working women tend to have fewer children than women who do not work) and the variation in family policies (Rodríguez-Pose, 2002).[73]

Figure 6.1: Spatial Distribution of Population Ageing



[73] For instance, the greatest effort to promote fertility has taken place in Sweden, while Ireland and Mediterranean countries have been less prone to try to increase the birth rate through family policies (Rodríguez-Pose, 2002: 83).

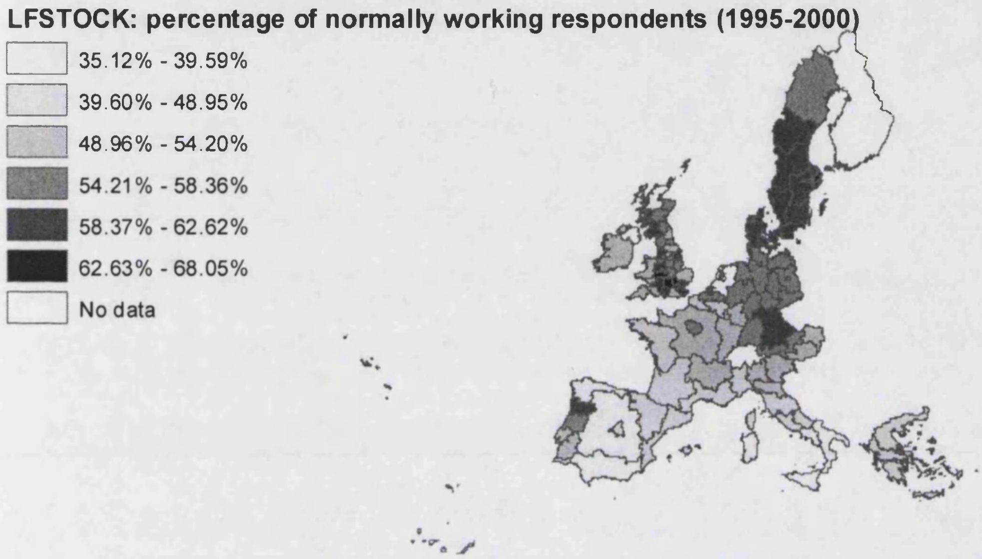
6.2.1.2 *Access to Work*

The effect of access to work on income and human capital distribution seems to be straightforward. Greater access to work is likely to lead to less income and educational inequality. Both theoretical and empirical evidence has been presented in support of this direction in the relationship. It is worth noting that access to work does not necessarily mean full-time work, but also might indicate atypical employment such as part-time work, temporary or limited-contract work, self-employment and the informal or shadow economy (i.e. family work, illegal forms of economic transactions). According to Rodríguez-Pose (2002), there is an age and gender divide in atypical employment forms, because the number of women working part-time is higher than that of men, whose part-time employment is concentrated among the young and the over 55s, while self-employment is basically a male phenomenon. He also states that atypical forms of employment not only determine income inequalities, but also affect educational inequalities, because people with lower skills are being relegated to these forms of employment and condemned to lower salaries. There is no fair access to jobs for all, because there is no fair employment European regulation. The concern is whether the differences in access to work for different age groups and the gender divide in employment can be justified by inter-group differences in worker attributes, or whether these differences are the result of employment discrimination and unfair access to work (Borooah, 1999). For instance, Catholics in Northern Ireland were excluded from a range of industrial jobs (Smith and Chambers, 1991). Discriminating employers, by indulging their taste for discrimination, may not only earn a lower level of profits within a region, but also create a higher level of income inequality. To sum up, it is expected that there is a trade-off between inequalities and work access, either due to the availability of full-time work or due to patterns in atypical employment.

The percentage of normally working respondents (*LFSTOCK*) represents the first (micro) proxy for access to work. The source of this variable is the ECHP dataset. This proxy is constructed from the variable '*Main activity status — Self-defined (regrouped)*'. Each person belongs to one of the following categories: (1) normally working (15+ hours/week); (2) unemployed; and (3) inactive. Figure 6.2 shows the geographical distribution of the percentage of normally working people within European regions. Sweden, Denmark, Greater London and its neighbours (i.e. Oxfordshire and Bedfordshire), Bayern and the Portuguese Norte have the highest percentage of normally working people in the EU. In contrast, the citizens of Spain

(Noroeste, Centro and Sur) and southern Italy (Campania, Sud, Sicilia and Sardegna) seem to have the lowest access to work opportunities. However, the employment rate is higher in the north than in the south (European Commission 1999). European citizens do not all have the same opportunities to engage in paid work, but rather there are considerable differences in people's access to work.

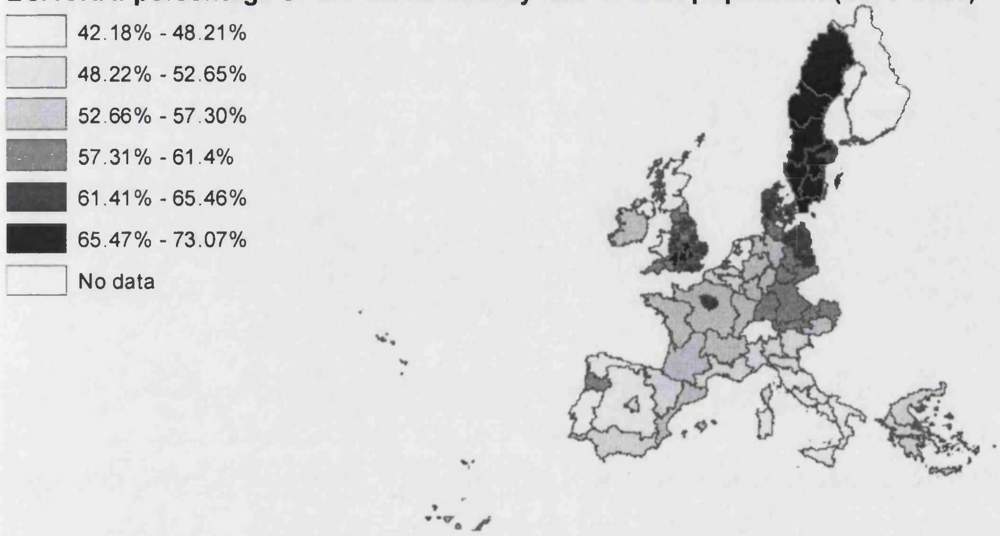
Figure 6.2: Spatial Distribution of Micro Proxy for Work Access



The second (macro) proxy for access to work is the percentage of economic activity rate for total population (*ECACRA*), taken from the Eurostat's Regio dataset. Figure 6.3 shows the spatial distribution of this proxy. It is similar to the distribution of the micro proxy. More specifically, there is an EU north-south divide, as the economic activity rate is higher in northern countries (Sweden, Denmark and Germany) than in southern ones (Greece, Italy, Spain). In addition, large urban areas exhibit higher economic activity rates than their respective national averages. One explanation for the relatively higher economic activity rates in large urban centres compared to other areas in the EU is probably related to the higher level of atypical employment in urban areas as compared to rural ones. For instance, students who simultaneously work part time are more often found in cities than in rural areas, because most universities are located in urban areas. Another explanation is that cities attract highly-qualified migrants in search of better working prospects. People move to urban areas in search of better educational opportunities, better employment and further career prospects.

Figure 6.3: Spatial Distribution of Macro Proxy for Work Access

ECACRA: percentage of economic activity rate of total population (1995-2000)



Men and women do not have the same opportunities to engage in paid work. Women have limited access to the labour market. There are considerable differences in men's and women's access to work. The causes of gender inequality in the EU labour market are quite complex, with a variety of political, administrative and legislative responses implicated (Barnes et al., 2005). Women have more responsibilities for care-giving and household tasks than their male partners. Many women, particularly those who are heads of households with young children, are either unemployed or limited in their employment opportunities for reasons that include inflexible working conditions and arrangements, inadequate sharing of family responsibility and a lack of sufficient services such as child care.[74] Many women stop working altogether after their having their first child, while others return to the labour market as part-time workers or when their child or children are of school age (Rodríguez-Pose, 2002: 80). The cultural barriers, including the persistence of informal networks from which women are excluded, also prevent them from achieving equal participation in the labour market (Court, 1995). Additionally, the effect of women's individual characteristics which shape their access to labour market may depend on the sociopolitical structure, such as the male dominated hierarchy of the political economy and the existing ideologies on gender (Coleman, 1991). According to Barnes et al. (2005: 171), gender inequalities at the regional level may reveal the predominance of women in part-time work, women's under-representation in sectors such as engineering and women's child-minding

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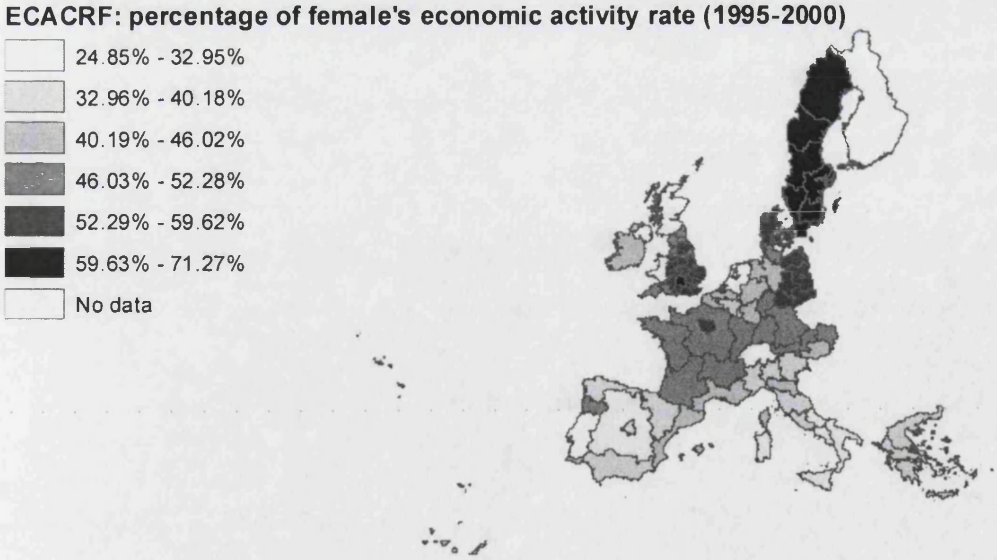
[74] www.iisd.ca/4wcw/dpa-045.html

responsibilities. High unemployment may discourage the participation of women in the labour market, so driving down the supply of labour (European Commission, 1999). Finally, high inactivity can be seen as an indicator of an unused pool of labour, particularly in the case of women (European Commission, 1999). Therefore, it is important to distinguish the female's work access effect from the total population's work access effect.

Women's access to work is measured as a percentage of the female economic activity rate (ECACRF), extracted from the Eurostat's dataset. Figure 6.4 illustrates the geographical distribution of females' work access. Sweden and Oxfordshire have the highest female participation in the labour market. The rate in Denmark, East Germany, Île de France and southern England is also high. The opportunity costs of child-bearing are greater in these societies (Rodríguez-Pose, 2002). On the contrary, Centro in Spain and southern Italy (Abruzzo-Molise, Campania, Sud, Sicilia and Sardegna) have the lowest rates of fenale economic activity. The female labour force participation rate increased between 1995 and 2000. This is most probably the result of the increasing flexibility within labour markets. Women are more able to access work opportunities. Women may have been more likely to have combined family responsibilities with paid employment in 2000 than in 1995.

Figure 6.4: Spatial Distribution of Female Work Access



6.2.1.3 Unemployment and Inactivity

Unemployment and inactivity are expected to be positively associated with income and educational 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, 1999). Additionally, unemployment insurance, welfare benefits and other forms of income support are usually not enough to offset the loss in income due to transitory unemployment. In other words, the income received through government transfer payments is lower than the income earned through employment.

The effect of unemployment and inactivity on income inequality also might reflect the inflexibility of the European labour market. European labour conditions, such as the degree of centralisation 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) are all important factors in accounting for the differences observed in income inequality across European regions. Labour market flexibility is responsible for changes in unemployment levels in western Europe and also has been linked to the reforms of specific labour market laws and of the welfare state (Rodríguez-Pose, 2002: 128).

From a broader perspective, the high level of structural unemployment which characterises most European societies is likely to cause a loss of current output and fiscal burden, a loss of freedom and social exclusion, skill loss and long-run damage, psychological harm, ill health, loss of motivation and organisational inflexibility, among other effects, which, in turn, increase income inequality (Sen and Foster, 1997).

It is widely acknowledged that individuals choose the optimal level of educational attainment by means of a marginal benefit-cost calculus, comparing the benefits derived from additional schooling to the costs incurred (Becker, 1964). Students from poorer backgrounds might not be able to choose the optimal level of educational attainment because of a lack of resources, low budget and low labour market information. First, students whose parents are unemployed or inactive (and thus have a low budget) are less likely to maximise their economic welfare by investing an appropriate amount in human capital. Second, students are not well informed about the nature and the prospects of the different education levels. In a market system, decisions are left to parents, at least for early education (Barr, 2004). However, parents with little education may have less information than better-educated parents about school choice and they may be less able to make use of any information that they do have (Ludwig, 1999; Barr, 2004). Therefore, children and teenagers from more affluent families have more accurate labour market information than children from unemployed and poor families.

More widespread access to education means that the better prepared are kept out of the labour market, leading to more youth unemployment (Rodríguez-Pose, 2002). Less-educated people have limited access to the labour market and are unlikely to find work even if there is an increase in the labour demand, because they do not possess the skills, or are in some way unsuitable, for the jobs on offer (European Commission, 1999).

The structure of the labour market is one of the underlying factors behind inequalities in the EU. Therefore, one key point of the analysis is to clarify whether unemployment and inactivity can explain part of the variation in income and educational inequality that cannot be explained by other determinants of inequality.

One the one hand, the underlying factor behind national and sub-national variations in inequalities due to a variation in unemployment might be differences in the regulation of European labour markets (Rodríguez-Pose, 2002). On the other hand, the regional unemployment differential across the EU may be explained by a non-regulatory framework. The main reason behind the persistence of regional unemployment in the EU is the mismatch between the educational supply and the labour demand, highlighting the employability of European workers (Rodríguez-Pose, 2002). The matching of the labour demand and supply in any region depends on the strength of its economic base and on the job content of growth (European Commission, 1999).

The unemployment and inactivity levels within a European region are measured using the variable '*Main activity status – Self-defined (regrouped)*' (ECHP dataset). *UNEM* denotes the percentage of unemployed respondents and *INACTIVE* is the percentage of inactive ones.

Figure 6.5 shows the geographical distribution of unemployment. It shows the spatial mismatch between the labour demand and labour supply. The Spanish region of Sur and the Italian regions Campania, Sud, Sicilia and Sardegna suffer from relatively high unemployment. The percentage of unemployed people in the Spanish region of Centro, the French Nord-Pas-de-Calais, the Italian Abruzzo-Molise and eastern Germany (Berlin, Brandenburg, Sachsen, Anhalt, Thüringen and Mecklenburg-Vorpommern) is also high. In these regions, there is a high percentage of people whose skills are either inadequate or are no longer demanded. Interregional differences in employment opportunities are concentrated among young people. High unemployment may discourage the participation of young people in the labour market and is likely to push them to continue their studies in order to gain more skills and knowledge. This drives down the supply of labour, at least in the short run. In the Spain of early 1990s, for instance, the level of education of the unemployed population was higher than that of the employed population, because more young people kept out of the labour market in order to continue their studies (Rodríguez-Pose, 1998). Moreover, persistently high unemployment in the EU has probably created a serious problem of marginalisation and social exclusion (Rodríguez-Pose, 2002: 118).

Low unemployment, by contrast, is found in Britain, in the Italian Nord-Est, in the Austrian Westösterreich and in the Portuguese regions of Norte and Centro. These regions display the highest rate of participation and activity in the EU. In these regions, demand matches labour supply and has kept pace with changes in it between 1995 and 2000. According to Rodríguez-Pose (2002: 118), long-term unemployment tends to be less of a problem in countries with more flexible (the United Kingdom) or more regulated (Scandinavia) labour markets. In Britain, for instance, labour market flexibility has been associated with the economic liberalism of the Thatcherite years. Britain has witnessed a high growth in part-time work on the part of mothers, as it means that more time can be devoted to childcare. Additionally, in the United Kingdom, the large differentials in income and employment conditions foster a substantial migratory flow from low income and high unemployment regions towards high income and low unemployment regions (Faini, 2003). Finally, in Europe, high unemployment regions tend to coincide with low income per capita and high income inequality regions.

Figure 6.5: Spatial Distribution of Unemployment

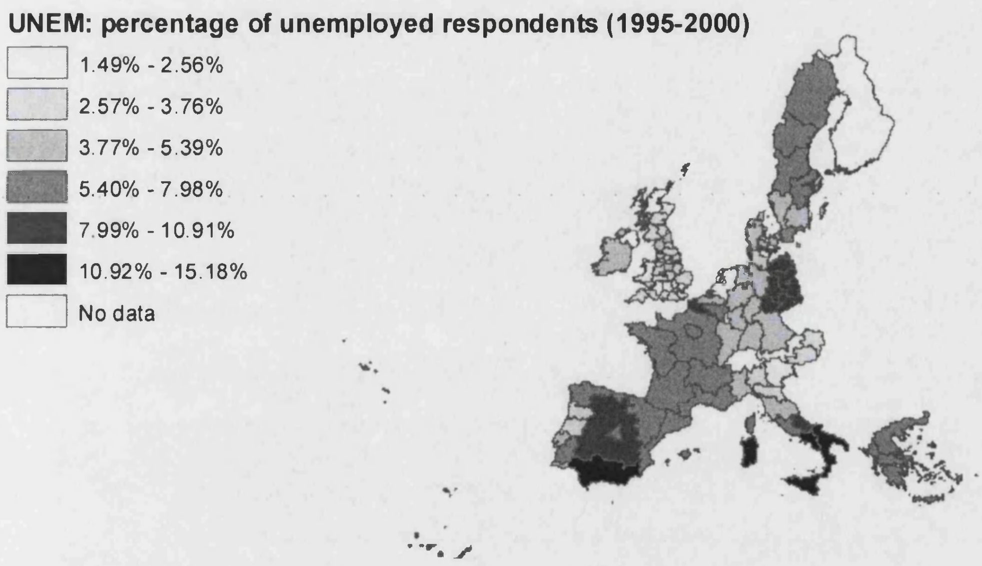
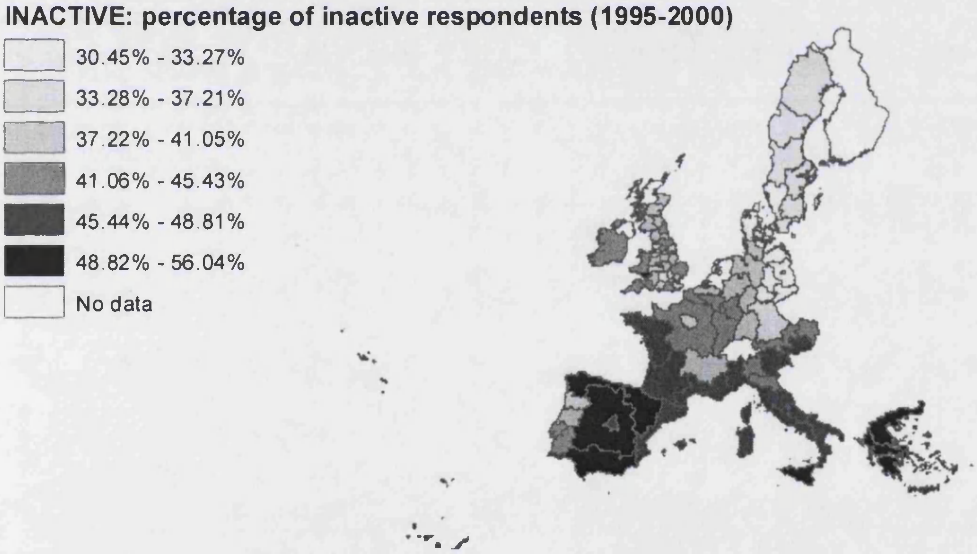


Figure 6.6 shows the spatial distribution of inactivity. This seems to be one of the main economic, social and political problems for the EU. Inactivity is higher in the south and lower in the north, representing an EU north-south divide. Greece and Spain have the largest inactive population in percentage terms, while eastern Germany and Denmark exhibit the lowest levels of inactivity. This is likely to illustrate the family structure of a country, because, according to the ECHP documentation, all members of a household are interviewed. More specifically, Sweden has the smallest average household size (2.2), while Spain and Greece are anong the largest (3.8 and 3.3, respectively) (Berthoud and Iacovou, 2004).

One of the most striking features of labour markets is the low percentage of activity in many European regions, especially in those where unemployment is high. However, the percentage of inactive east German respondents is relatively low, while the percentage of unemployed respondents in that same region is high.

Figure 6.6: Spatial Distribution of Inactivity



6.2.1.4 Summary Statistics

The transformed dataset with the percentage, standard deviation and minimum and maximum value for each of the labour related variable is displayed in Table 6.1.[75] The descriptive statistics show that the dataset is unbalanced, which is amenable to

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[75] Appendix A6.1 shows the descriptive statistics for the ECHP quantitative and qualitative variables.

estimation methods that manage the heterogeneity bias. This table shows the following evolutions.[76]

- Population ageing has increased slightly between 1996 and 2000.
- Work access has increased to some extent between 1997 and 2000.
- Unemployment has decreased between 1995 and 2000.
- Inactivity has not changed between 1995 and 2000.
- Women's work access has increased between 1995 and 2000.

Table 6.1: Summary Statistics of Time-variant Variables

Variable	Year	Source	Obs	%	Std. Dev.	Min (%)	Max (%)
AGE	1995	ECHP	94	45.19	2.29	39.76	51.39
	2000		102	45.96	1.86	42.32	51.35
	1995-00		596	45.40	1.95	39.76	51.61
LFSTOCK	1995	ECHP	94	52.27	0.07	33.59	67.78
	2000		102	53.79	0.07	36.56	67.55
	1995-00		596	52.78	0.07	31.20	72.88
ECACRA	1995	Eurostat	65	54.90	7.47	42.00	74.80
	2000		94	57.89	6.61	42.90	74.50
	1995-00		525	57.10	6.85	41.50	74.80
UNEM	1995	ECHP	94	5.80	0.03	0.00	16.54
	2000		102	4.46	0.03	0.59	14.85
	1995-00		596	5.28	0.03	0.00	16.54
INACTIVE	1995	ECHP	94	41.92	0.06	29.21	55.49
	2000		102	41.74	0.06	29.53	55.42
	1995-00		596	41.94	0.06	27.12	56.72
ECACRF	1995	Eurostat	65	44.78	10.82	24.00	72.20
	2000		94	49.15	9.14	26.70	72.90
	1995-00		525	47.79	9.52	23.40	72.90

Source: ECHP dataset and Eurostat's Regio dataset

6.2.2 *Other Variables*

The analysis performed here is focused on the role of urbanisation, geography and institutions.

6.2.2.1 Urbanisation

The economic theory has ambiguous predictions about the likely effects of urbanisation on income inequalities. Kuznets (1955) speculated that income inequality in developing

[76] The values from 1996–1999 are provided on request.

societies is typically higher in urban than in rural areas, highlighting the positive association between income inequality and urbanisation. On the positive relationship, Haworth et al. (1978) pointed out that the principal beneficiaries of increasing urbanisation will be those individuals who possess 'monopoly' advantages in the marketplaces, and thus, the benefits from increasing urbanisation will be unequally distributed and cause income inequality to rise. To this end, Nord (1980) stressed that as large cities, and thus urbanisation, attract both highly paid professional workers and many displaced workers and immigrants, the changing occupational and wage structure is likely to worsen inequality.

Considering the negative relationship between urbanisation and inequality, Frech and Burns (1971) and Burns (1975) argue that the functioning of capital markets will improve as city size increases, so that investment in human capital will rise and the average rate of return will be depressed to reduce inequality. Yorukoglu (2002), based on simulation results using Lucas' (2001) model, shows that the declining inequality of productivity across locations of cities due to suburbanisation can account for a substantial portion of the decrease in income inequality. The formation of cities has created positive externalities that increase the economic chances and opportunities of poor people. Low income inequalities and the urban agglomeration of socioeconomic activities seem to be mutually self-reinforcing processes. Lower income inequality, through higher economic opportunities, spurs the urban agglomeration of economic activities, which in turn leads to a lower cost of innovation, higher investments and lower income inequality, so that a circular causation between income inequality and urbanisation sets in. Urbanisation, on the one hand, and inequality, on the other, are parallel processes. Additionally, city sizes and human capital levels vary across city-types. For instance, cities specialising in financial, business, or diversified services are significantly larger (like London) than traditional manufacturing cities. The former type have much greater levels of educational attainment than the latter.

Taking into consideration the most recent empirical studies, Nielsen and Alderson (1997) examined the determinants of income inequality in approximately 3,100 counties of the United States in 1970, 1980 and 1990 and found a positive effect of urbanisation on inequality. Partridge et al. (1996) also show that a positive metropolitan-inequality relationship is expected if a prevalence of service-producing industries (i.e. financial services) with a bimodal wage distribution are centred in metropolitan areas. Additionally, Estudillo (1997) argued that income distribution within the urban population is wider than that of the rural population because of the heterogeneity of the urban group. Bourguignon and Morrisson (1998) and Motonishi (2006) find that the household share of agricultural and non-agricultural sectors, as a proxy of the urbanisation ratio, also positively affects income inequality. This means that income distribution between the agricultural and non-agricultural sectors can explain a part of the total income distribution. Hence, they are concerned about the impact of economic dualism on income inequality.

There is less empirical evidence on the effect of urbanisation on educational inequality. The relationship between urbanisation and educational inequality is addressed through the relationship between urbanisation and income inequality, and vice versa. Glaeser (1999), for instance, has suggested that urbanisation influences the wages, and thus incomes, of different workers in different ways as a result of learning, knowledge and skills. He points out that urban density may be negatively associated with wage dispersion, because low-skilled workers may have more to gain through learning than high-skilled workers. Wheeler (2004) has also offered some evidence on this relationship.

Information about labour markets has an impact on urban-rural differences in educational inequality. People who live in low-income rural areas have usually less accurate information about labour market institutions than people in high-income urban areas. There is no horizontal equity in education between urban and rural citizens, because the problem of lacking information is greater for individuals in lower socioeconomic and rural groups as information is costly to acquire (i.e. due to distance). Since information has a positive influence on educational attainment (Ludwig, 1999), and educational attainment and educational inequality are negatively correlated, low-income rural areas have not only low educational attainment, but also high educational inequality.

The levels of income and educational inequality in urban and rural areas have evolved differently. Therefore, the process of explaining income and educational inequality differences across regions of different densities is quite complex.

Urbanisation within a region is measured as the percentage of respondents who live in a densely populated area ($URBANDPAV$), taken from the ECHP data survey. This variable is treated as time-invariant, because the availability of data is time limited (1999 and 2000). Unfortunately, there are only data available for Austria, Belgium, Denmark, Greece, Ireland, Italy, Portugal and the United Kingdom, corresponding to 63 regions.

6.2.2.2 Geographical Variables such as Latitude

The ESDA on income and educational inequality (Chapters 3 and 4, respectively) has addressed latitude as a major determinant of inequalities, underpinning the EU north-south divide and the regional polarisation in the EU. Inequality has evolved differently in northern and southern areas. More specifically, high inequality clusters are mainly in the south, while low inequality clusters centre on the north. Latitude, which is regarded as a characteristic of the 'first' nature of geography (physical geography), seems to be an important source of differences in income and human capital. It is likely to play an important role in shaping the European distribution of income and educational. Past studies of the relationships between regional economic activity and geography have been hampered by using dummies to classify the location of each region (i.e. Baumont et al., 2003; Fischer and Stirbock, 2006; Monastiriotis, 2006). However, the allocation of some regions to the north-south regime is arbitrary and should be tested according to alternative definitions of 'north' and 'south'. So as to avoid the arbitrary regional allocation and partly as a result of the identified limitations of the existing literature in examining the impact of latitude on inequalities and on economic activity in general (i.e. Gallup et al., 1999; Acemoglu et al., 2001; Mitchener and McLean, 2003; Woods, 2004; Olsson, 2005), the analysis performed here is an attempt to fill this gap. Adam Smith made a notable hypothesis that the physical geography of a region can influence its economic performance. Mitchener and McLean (2003), for example, have found that latitude accounts for a low proportion of the differences in productivity levels in the United States. However, Woods (2004) shows that latitude is a key analytical concept in understanding the spatial aspects that effect economic development.

Latitude is a good proxy for the effects of a region's climate on its level of productive efficiency (Mitchener and McLean, 2003). Climatic variation affects productivity for three reasons. First, disease ecology, agronomic processes and soil fertility can be influenced by climate and may, in turn, alter productivity (Mitchener and McLean, 2003). For example, temperate climates favour productivity and thus inequalities and economic growth. Second, good weather is an amenity. For instance, cities with better weather than that of their countries in general have systematically higher rates of urban population growth (Cheshire and Magrini, 2006). Third, changes in the occupational and wage structure are not independent of weather. For instance, income inequality is higher in the Mediterranean countries which have many tourist resorts (i.e. the Greek islands) that offer part-time jobs, especially in the summer and for women and young people.

It is worth noting that classifying regions according to the north-south regime may lead to theoretical considerations based on the 'second' nature of geography (the geography of distance between economic agents) such as the NEG and the club convergence theories. Thus, while latitude is a variable of physical geography, the analytical concepts that are crucial in understanding the relationship between latitude and inequalities may not be a matter of the 'first' nature of geography. The analysis performed here goes beyond the distinction between the 'first' and the 'second' nature of geography. However, most existing studies which consider latitude clearly as a variable of physical geography are implemented at the national level. Gallup et al. (1999) and Sachs et al. (2001), for instance, have found that nations in tropical climate zones generally suffer from higher rates of infectious diseases and lower levels of agricultural productivity than do nations in temperate zones. To sum up, latitude is likely to account for a high proportion of the differences in regional inequality levels.

6.2.2.3 Some Institutional Variables

The variables explored here organise regions into categories that are hypothesised to have some underlying similarity with regard to institutions, such as welfare regimes, religion and family structure. The welfare state, religion and family structure approach allows the examination of cross-national and cross-regional differences without focusing on the idiosyncrasies of single countries and regions. The goal here is to investigate the effects of more general institutional and cultural arrangements (DiPrete and McManus, 2000; Stier et al., 2001). This approach is more concise than using country-dummies.

(1) The Welfare State

The mechanisms through which income and human capital inequalities are reproduced vary across the welfare states. The objectives of the welfare states are economic efficiency, social justice (equity) and administrative feasibility (Barr, 2004). The welfare state comprises both cash benefits (i.e. income) and benefits in kind (i.e. education) (Barr, 2004). Although the level of welfare is reflected in areas such as power, industrialisation and capitalist contradictions, social expenditure can be considered a good proxy of a state's commitment to welfare (Esping-Andersen, 1990). Following the work of Esping-Andersen (1990), Ferrera (1996) and Berthoud and Iacovou (2004), four categories of welfare state are used: social-democratic (Sweden, Denmark), liberal (United Kingdom, Ireland), corporatist or conservatism (Luxembourg, Belgium, France, Germany, Austria) and 'residual' or 'southern' (Portugal, Spain, Italy, Greece) (Figure 6.7). This classical categorisation focuses on the relationship between the state and the market with respect to the provision of income and services and considers the effects of welfare states on social stratification and socioeconomic inequalities (Geist, 2005: 25). The hypothesis here is that a country's welfare policy as measured through its social expenditures has a significant effect on income redistribution and, thus, on income inequalities.

Although the boundaries of the welfare states are not well defined, 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: 28). More specifically, the social-democratic and the corporatist regimes have well-developed welfare states and offer a more state provision for income and services than do liberal regimes (Orloff, 1996). However, the social-democratic regimes are 'universalistic and egalitarian' (Orloff, 1993) and it is the individual that is placed at the centre, as benefits and taxes are mainly individually based (Svallfors, 2004), while the conservative regimes seek to maintain status differences and the role of the family is emphasised. In the liberal welfare states the market is the prime source of resources and interests (Svallfors, 2004) and like the social-democratic states, these states focus on the individual. The liberal welfare states are the most market-oriented ones. In Britain, for instance, there is no national form of income-related social insurance, but a universal child benefit and public health care are provided free of charge (Svallfors, 2004: 122). Finally, in the 'residual' welfare states, the share of national income devoted to social purposes is very low; the level of benefits is meagre and covers the minority of population (Sainsbury, 1991). It is important that the impact of EU social policy on the development of the 'residual' welfare states should be taken into account, because Portugal, Spain and Greece all benefit from structural and cohesion funds (Guillen and Alvarez, 2004; Guillen, 2005).

The welfare regime shapes women's access to work, because the patterns of division of household labour vary across welfare state regimes. The social-democratic regimes encourage women's participation in the labour market. The availability of public care services to families has an influence on women's life choices by enabling them to have both children and careers (Esping-Andersen, 2002). In the Swedish case, for instance, domestic role-sharing between men and women is encouraged (Geist, 2005). In liberal regimes, '*gender equality is not as actively pursued as it is in the social-democratic regimes*' (Geist, 2005: 26). Conservative regimes, by contrast, support traditional gender roles. Women are encouraged to stay at home while the children are small. Women are encouraged to do more housework than men, even when this means a reduction or modification of their labour force participation. In Germany, for instance, women are discouraged from participating full-time in the labour market, a move that is clearly demonstrated by the shortage of public day care and the fact that family supplements and tax deductions are used to support men's income, as it is he that is seen as the family provider (Sundström, 2002). Additionally, conservative regimes are influenced by the social policy of the Catholic Church (Geist, 2005: 26). The family and the Catholic Church are responsible for solving social problems, and the conservative welfare state intervenes only if those institutions have failed (Borchorst, 1994). Therefore, the welfare state, and in some cases the religion, can create a framework that is more conducive to specific arrangements of domestic labour (Geist, 2005: 26).

Thus, welfare state regimes not only represent different types of relationship between the state and the labour market, but also the different ways that highly developed societies address income and human capital inequalities.

Figure 6.7: Spatial Distribution of Welfare State Types

(2) Religion

Going back to Weber (1922), religion, as an aspect of social life and culture, distributes social rewards and shapes life chances. Religion concerns 'non-market' activities and institutions (Iannaccone, 1992). It affects the economic attitudes and activities of individuals, groups (i.e. the members of a household) and societies (i.e. regions). Religion may also influence not only individual earnings and the rate of return on human capital as has already been examined by many scholars (Greeley, 1976; Tomes, 1983, 1984, 1985; Iannaccone, 1992, 1998a, 1998b), but also levels of income and human capital inequality. The religious affiliation of European regions is classified into four Christian categories:[77] 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) (Figure 6.8). Cross-region differences in the impact of income and human capital distribution on religious belief may explain the cross-region variation in the inequality-religion connection. On comparing the spatial distribution of inequalities (both income and human capital) with the distribution of religions, it appears that the relationship between inequality and religious affiliation fluctuates highly across regions.

Might different Christian religions affect regional economic welfare differently? Which religions exert the strongest influence? Although the relationship between religion and inequality is tremendously complex, it is hypothesised that regions with the same religion have close social links, leading to similar income and human capital inequality levels within-groups of religion, but different inequality levels between-groups of religion. Nevertheless, there are some significant differences even within each religion category. For instance, the boundaries that separate fundamentalist Protestants from mainstream Protestants remain sharp. Fundamentalist Protestant women enter marriage at a younger age and display a lower level of attachment to the labour market when young children are present in the home than women of mainstream Protestant affiliation (Lehrer, 1995), increasing the probability of greater inequalities. Moreover, fundamentalist parents are willing to invest fewer funds in the education of their children, increasing the intergenerational inequality (Lehrer, 1995).

[77] 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

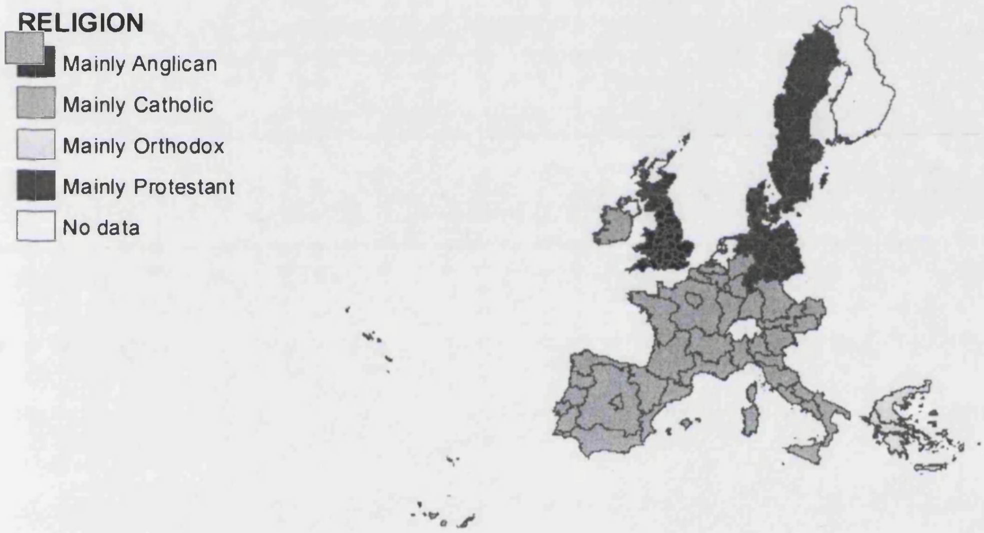
In the analysis performed here, I examined whether the religion in which individuals are brought up influences their income and their education. Various channels through which religion may influence the level of income and education have already been considered, such as marriage and divorce, fertility and childrearing (Iannaccone, 1998a, 1998b). Religious also leads to differences in earnings, education and the female employment (Lehrer, 1996, 1999). According to Keister (2003), religion affects wealth ownership by shaping demographic behaviours, identifying which goals should be valued and contributing to social contacts that provide information and opportunities. Additionally, religion influences the processes that create wealth and educational inequalities through attitudes towards work (Heath et al., 1995), family traditions and cultures (Tomes, 1983; Swidler, 1986), the creation and implementation of public institutions such as blue laws and prohibition (Fairbanks, 1977) and the party competition (Hutcheson and Taylor, 1973). Therefore, religion plays a significant role in the creation of both the private and public institutions that affect inequalities. The magnitude of the differences among Christian religious groups in the determination of income and human capital inequalities is used as a control variable in the analysis.

Religion may be an important determinant of how people think about inequalities (Feagin, 1975). Protestants and Catholics hold the strongest individualistic beliefs, which locate the causes of low income and human capital stock in the people themselves (i.e. lack of ability, lack of effort), but are weakest in terms of structuralist beliefs, which locate the causes of low income in the social and economic system (i.e. lack of jobs, discrimination) (Hunt, 2002). It is not only the religious affiliation, but also the education level completed that determines beliefs and how people think about the causality effects underlying the various types of inequality. More highly-educated people tend to favour individualistic explanations, while the beliefs of less highly-educated persons are typically structuralist (Hunt, 2002).

The religious affiliation of European regions is mainly Christianity. Christianity encourages laissez-faire capitalism and economic development, but according to the secularisation hypothesis, economic development reduces religious participation and beliefs (McCleary and Barro, 2006). Economic development increases the value of time and implies a rising opportunity cost of participating in time-intensive activities, such as religious services (McCleary and Barro, 2006: 152). Thus, higher regional economic development and more intensive competition are likely to reduce attendance of formal religious activities. However, it is often believed that Catholicism is less conducive to economic development than Protestantism (Grier, 1997: 48). With respect to education, on the one hand, highly-educated people are more scientific and are more inclined to reject beliefs that posit supernatural forces (McCleary and Barro, 2006: 151), while, on the other hand, educational attainment increases the returns from networks and other forms of social capital including religious services (Sacerdote and Glaeser, 2001). Education both increases the returns to social connection and reduces the extent of religious belief (Sacerdote and Glaeser, 2001). For example, less-educated people are more likely to believe in miracles, heaven and devils.

To sum up, it is expected that religion plays no small role in income and human capital inequalities.

Figure 6.8: Spatial Distribution of Religion



(3) Family Structure

The concept to family structure that I use in this analysis refers to the household size. Since all persons within a household are interviewed, the household size, which differs across regions, might be a significant explanatory variable in inequalities. Following the work of Berthoud and Iacovou (2004), three groups of countries in the study of living arrangement are used: Nordic (Sweden, Denmark), North/Central (UK, Belgium, Luxembourg, France, Germany, Austria) and Southern/Catholic (Ireland, Portugal, Spain, Italy, Greece) (Figure 6.9). The hypothesis is that a country's family structure plays a significant role in income and human capital inequality.

Broadly speaking, there are three different living arrangements:

1. Living with unrelated individuals: This type of household means sharing living quarters with unrelated persons (i.e. students) and does not imply sexual relations between housemates.[78] In this case, householders tend to choose housemates with incomes similar to their own and with the same educational level (Leppel, 1987). This implies that the intra-household income and human capital inequality is very low.

2. Living alone (i.e. unmarried, widowed and divorced): In this case, individual inequalities coincide with household inequalities.

3. Living with related individuals: In societies where the husband is expected to support the wife who usually serves as full-time homemaker, the husband's wage must be large enough to support two adults (Leppel, 1987). Additionally, the husband's pension entitlement covers his wife. In this case, the intra-household income inequality is high and it is even higher when the husband must support children. One should bear in mind that inequality index for households is always lower than for individuals because of income pooling and intra-family transfers. Fertility is one of the most significant determinants of family structure. In these societies, marriage is usually delayed until the man is in a sufficiently strong financial position (Leppel, 1987). In societies where women are labour force participants, the spouse shares the living expenses and the intra-household income inequality is low. The 'living with related individuals' household also includes householders living with siblings. With regard to education, the larger the household size, the higher the intra-household educational inequality as rich people have usually less children than poor people. A particular case in this type of household is the single-parent family. Many scholars (McLanahan, 1985; Sandefur et al., 1992; Sandefur and Wells, 1999) have all pointed out that individuals who grow up in a single-parent family are less likely to graduate from high school than those who grow up in a family with both original parents. Studies show that the family relations and climate influence the educational attainment. Elder (1965: 83), for instance, showed that:

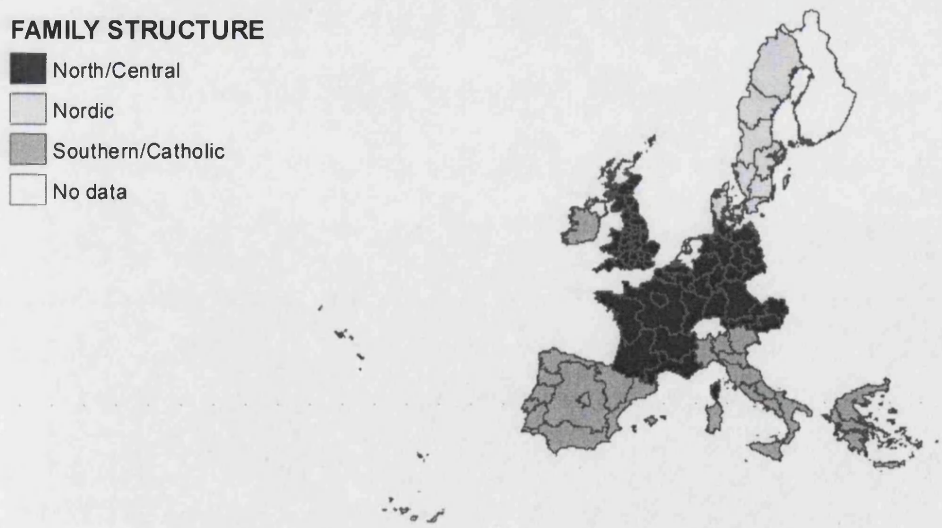
[78] People live together rather than apart, because the cost per person of a given standard of living is lower.

'educational attainment is negatively related to the degree of parental dominance in adolescence... high educational attainment is most prevelant among persons who report democratic relations with their parents and egalitarian relations between mother and father... parent-youth relations have a greater effect on educational attainment than conjugal role patterns'.

Therefore, in regions where most people live with related individuals, individual inequality is higher than household inequality and is even higher when the wife is not a participant in the workforce and there are many children. In regions, by contrast, where most people live alone or with unrelated persons, there is not much difference between individual and household inequality. Additionally, people living in larger and younger households are typically poorer, while a larger household size may make at least some members better off; for example, it may offer greater security in old age (Lanjouw and Ravallion, 1995: 1415).

It has been demonstrated that marriage, divorce, fertility and childrearing influence the level of religious beliefs, activities, affiliation and participation. Religion can be a significant defining trait of a family (Keister, 2003: 176). For instance, a religion where fertility is relatively low decreases the household size. Additionally, the welfare state indirectly determines the household size because, for instance, a socialist welfare state supports female participation in the labour market.

Figure 6.9: Spatial Distribution of Family Structure



6.3 Regression Results for Income Inequality

This section explores the determinants of income inequality. Static and dynamic approaches allow us to assess whether a number of determinants are instrumental in explaining the variation in income inequality and to identify the influences that persist or wane.

The first subsection explores the determinants of *income inequality for the population as a whole*

$$IGE1_{it} = \beta_1' IMN_{it} + \beta_2' EducAtt_{it} + \beta_3' EducIneq_{it} + \beta_4' x_{it} + u_{it}$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...,6$).[79] $IGE1_{it}$ is income inequality for the population as a whole, IMN_{it} is income per capita for the population as a whole, $EducAtt_{it}$ is educational attainment (either average education level completed (EMN_{it}) or average age at which the highest education level was completed (AMN_{it})), $EducIneq_{it}$ is educational inequality (either inequality in education level completed ($EGE1_{it}$) or inequality in the age at which the highest education level was completed ($AGE1_{it}$)), x_{it} is a vector of control variables, $\beta_{1,...,4}$ are coefficients and u_{it} is the composite error.

Table 6.2 shows the code and definition of control variables.

Table 6.2: Control Variables

a/a	Variable	Definition
1	AGE	Population ageing
2	LFSTOCK	Work access (micro approach)
3	ECACRA	Work access (macro approach)
4	UNEM	Unemployment
5	INACTIVE	Inactivity
6	ECACRF	Female's work access
7	URBANDPAV	Urbanisation (time-invariant)
8	LAT	Latitude (time-invariant)
9	Welfare state	
	DWSSOC	Socialism (social-democratic)
	DWSLIB	Liberal
	DWSCORP	Corporatist (conservatism)
	DWSRES	Residual ('southern')
10	Religion	
	DRLPROT	Mainly Protestant
	DRLCATH	Mainly Catholic
	DRLORTH	Mainly Orthodox
	DRLANGL	Mainly Anglicans
11	Family structure	
	DFNORD	Nordic (Scandinavian)
	DFNC	North/Central
	DFSC	Southern/Catholic

The second subsection explores the determinants of *income inequality for normally working people*.

$$NGE1_{it} = \beta_1' NMN_{it} + \beta_2' EducAtt_{it} + \beta_3' EducIneq_{it} + \beta_4' x_{it} + u_{it}$$

[79] $t = 1$ denotes 1995, ..., $t = 6$ denotes 2000.

where $NGE1_{it}$ is income inequality for normally working people and NMN_{it} is income per capita for normally working people. This equation does not include the control variables 2–5 (work access, unemployment and inactivity) listed in Table 6.2, because the dependent variable concerns working people.

More specifically, in Table 6.3–Table 6.10 Regression 1 shows the linear impact of income per capita on income inequality. Regression 2 displays the introduction of human capital distribution measured by educational attainment and educational inequality. Regression 3 tests for the influence of the population ageing.

Considering the determinants of *income inequality for the population as a whole* (Table 6.3–Table 6.6), two different proxies for access to work are included in Regressions 4 and 5. The addition of unemployment and inactivity, as well as of women's access to work, is explored in Regressions 6 and 7. The next step of static analysis is the introduction of quantitative and qualitative time-invariant variables (Regressions 8–12). Regressions 8 and 9 represent a preliminary test for the urban-rural and the EU north-south patterns, which have been identified in ESDA. These patterns are tested using the following quantitative explanatory variables: urbanisation and latitude. Finally, welfare-state, religion and family-structure dummies (qualitative variables) are added in Regressions 10, 11 and 12, respectively.

On considering the determinants of *income inequality for normally working people* (Table 6.7–Table 6.10), work access of the total population, unemployment and inactivity are excluded from the analysis. Hence, Regression 4 of both static and dynamic models estimates the impact of women's work access on income inequality. Regressions 5 and 6 of the static models introduce urbanisation and latitude as explanatory variables, respectively. The above-mentioned dummies are included in Regressions 7, 8 and 9.

6.3.1 Income Inequality for the Population as a Whole

6.3.1.1 Independent Educational Variable: Education Level Completed

(a) Static model

In all the regressions of income inequality for the population as a whole, the p-values of Breusch and Pagan's Lagrange multiplier test strongly reject the validity of the pooled OLS models, and the p-values of Hausman's test reject the GLS estimator as an appropriate alternative to the FEs estimator. Although the distinction between FEs and REs models is an erroneous interpretation (Greene, 2003), according to the specification tests, the FEs models are the most appropriate. Finally, there is not 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 of the error term. Table 6.3 displays the FEs regression results, while the OLS and REs results are displayed in Appendices A6.3 and A6.11, respectively.

Table 6.3: FEs: Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMN	-0.0001 (0.0011) _(0.0013)_	0.0016 (0.0014) _(0.0016)_	0.0026 (0.0014)* _(0.0017)_	0.0033 (0.0014)** _(0.0017)_*	0.0029 (0.0016)* _(0.0017)_*	0.0046 (0.0016)*** _(0.0017)_***	0.0039 (0.0016)** _(0.0018)_**	0.0110 (0.0025)*** _(0.0027)_***	0.0111 (0.0019)*** _(0.0021)_***
EMN		0.0396 (0.0305) _(0.0316)_	0.0394 (0.0303) _(0.0318)_	0.0466 (0.0301) _(0.0309)_	0.0018 (0.0306) _(0.0293)_	0.0136 (0.0298) _(0.0276)_	0.0101 (0.0305) _(0.0285)_	0.0222 (0.0396) _(0.0415)_	0.0103 (0.0314) _(0.0277)_
EGE1		0.0723 (0.0230)*** _(0.0231)_***	0.0732 (0.0229)*** _(0.0232)_***	0.0685 (0.0227)*** _(0.0223)_***	0.0313 (0.0224) _(0.0197)_	0.0330 (0.0218) _(0.0184)_*	0.0361 (0.0222) _(0.0188)_*	0.0831 (0.0302)*** _(0.0374)_**	0.0424 (0.0211)** _(0.0163)_***
AGE			-0.0057 (0.0022)** _(0.0024)_**	-0.0059 (0.0022)*** _(0.0026)_**	-0.0082 (0.0022)*** _(0.0025)_***	-0.0053 (0.0022)** _(0.0025)_**	-0.0073 (0.0022)*** _(0.0024)_***	-0.0073 (0.0027)*** _(0.0026)_***	-0.0030 (0.0022) _(0.0023)_
LFSTOCK				-0.2765 (0.0837)*** _(0.0981)_***					
ECACRA					-0.0089 (0.0014)*** _(0.0016)_***				
UNEM						0.5541 (0.1404)*** _(0.1515)_***		0.4594 (0.2069)** _(0.2305)_**	0.3783 (0.1378)*** _(0.1511)_**
INACTIVE							0.0084 (0.0933) _(0.1080)_		
ECACRF						-0.0068 (0.0012)*** _(0.0013)_***	-0.0079 (0.0012)*** _(0.0013)_***	-0.0020 (0.0017) _(0.0017)_	-0.0042 (0.0012)*** _(0.0014)_***
YR96*URBANDPAV								-0.0290 (0.0148)* _(0.0151)_*	
YR97*URBANDPAV								-0.0453 (0.0150)*** _(0.0136)_***	
YR98*URBANDPAV								-0.0136 (0.0163) _(0.0147)_	
YR99*URBANDPAV								-0.0374 (0.0174)** _(0.0170)_**	
YR00*URBANDPAV								-0.0743 (0.0184)*** _(0.0171)_***	
YR96*LAT									-0.0002 (0.0001) _(0.0001)_
YR97*LAT									-0.0005 (0.0001)*** _(0.0001)_***
YR98*LAT									-0.0003 (0.0001)*** _(0.0001)_***
YR99*LAT									-0.0006 (0.0001)*** _(0.0001)_***
YR00*LAT									-0.0009 (0.0001)*** _(0.0002)_***
CONSTANT	0.3821 (0.0121)*** _(0.0151)_***	0.2787 (0.0382)*** _(0.0396)_***	0.5255 (0.1022)*** _(0.1072)_***	0.6732 (0.1106)*** _(0.1220)_***	1.2128 (0.1333)*** _(0.1438)_***	0.8348 (0.1195)*** _(0.1213)_***	1.0108 (0.1153)*** _(0.1182)_***	0.6300 (0.1611)*** _(0.1640)_***	0.5593 (0.1288)*** _(0.1337)_***
ADJ R-SQ	0.0000	0.0313	0.0445	0.0654	0.1343	0.1743	0.1432	0.2704	0.2601
OBS.	604	596	596	596	513	513	513	299	513
LM TEST (p-value)	916.46 (0.0000)	715.20 (0.0000)	645.03 (0.0000)	634.09 (0.0000)	715.68 (0.0000)	676.43 (0.0000)	630.60 (0.0000)	322.72 (0.0000)	694.28 (0.0000)
HAUSMAN TEST (p-value)	71.46 (0.0000)	289.07 (0.0000)	35.86 (0.0000)	87.27 (0.0000)	46.71 (0.0000)	54.24 (0.0000)	73.32 (0.0000)		

Note: (*), (**), and (***) indicates significance at the 10%, 5% and 1% level, respectively. _(*), (**),_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

In Regression 1, the impact of income per capita (*IMN*) on income inequality (*IGE*1) is analysed. This equation is unconditioned by any other effects. The relationship between income per capita and inequality is negative, 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 FEs conditional regressions (Regressions 3–9) income per capita is positively correlated with income inequality. The higher the income per capita, the higher the inequality within a region. A few people can be transferred to higher levels of skills, while the remainder have to wait their turn (Lydall, 1979). Regional economic development seems to increase the occupational choices and the earning opportunities of rich people. In all the regressions, however, the coefficients on income per capita are very low. For instance, Regression 4 shows that an increase of one per cent in income per capita is associated with, on average, about 0.0033 per cent more income inequality, as measured by the Theil index. The findings also indicate that the effect of income per capita on inequality is robust as it is not sensitive to the model specification.

The next step in the analysis is the introduction of human capital distribution, as measured by educational attainment (*EMN*) and educational inequality (*EGE*1). Regressions 2–9 indicate that regional educational achievement probably has no influence on the resulting income distribution, because the coefficients on educational attainment are not statistically significant. Thus, it is not clear whether higher educational attainment increases the occupational choices and the earning opportunities of the population as a whole so as to make societies more egalitarian. Additionally, it is not clear whether education serves to facilitate numerous favourable chances for individuals, because it reflects abilities, choices and preferences (Hannum and Buchmann, 2005). The insignificant correlation between income inequality and educational attainment also says nothing about the balance between the 'wage compression' effect and the 'composition' effect (Knight and Sabot, 1983). Education does not seem to expose all economic agents to a common shift factor that affects each individual's income. The empirical results, nonetheless, show that a highly unequal distribution of education level completed is associated with higher income inequality. This relationship is robust and statistically significant (Regressions 2–4 and 6–9). A larger share of highly-educated workers within a region may signal to employers that those with less education have less ability, which may also lead to a larger wage differential between highly-educated and less-educated workers and thus to higher income inequality. An increase in the levels of education of the highly-educated people tends to increase income inequality as the imperfect competition for positions requiring advanced educational credentials raises the wages of educated people even more. 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 indicate the responsiveness of the EU labour market to differences in qualifications and skills.

The remaining regressions include the control variables described earlier. Regressions 3–9 test for the influence of the average age of respondents (AGE). 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 a labour market that rewards seniority, increasing the inequality levels within a society (Higgins and Williamson, 1999). As the European population gets older, income inequality decreases, because the elderly and retired people whose income is higher than the mature working age cohort have obtained the necessary credentials when they were younger and they usually do not intend to acquire higher education so as to improve their economic circumstances even more. Hence population ageing seems to matter for income inequality.

In order to capture the economic activity characteristics of the regions, the percentage of normally working respondents $(LFSTOCK)$, and the economic activity rate of the total population $(ECACRA)$ are included in Regressions 4 and 5, respectively. As expected, both variables are negatively associated with income inequality and are statistically significant. The higher the level of 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 the participation in labour market by sex $(ECACRF)$ in Regressions 6 and 7, respectively. The results indicate that high unemployment is associated with higher income inequality. Increases in unemployment 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, 1999). Additionally, unemployment insurance, welfare benefits and other forms of income support are not enough to offset the loss in income due to the transitory unemployment. European labour conditions, such as the degree of centralisation 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 benefits, job-creation policies and vocational training programmes (Ayala et al., 2002), represent an important factor in determining the differences observed in income inequality across European regions. The coefficients on the female economic activity rate in all regressions are negative and significant. The impact of the increase in women's access to work 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). The fact that income inequality among normally working people declined slightly throughout the period of study is most probably a reflection of the greater flexibility of working conditions and arrangements for women, the more adequate sharing of family responsibility and the more adequate childcare services. Both men and women seem to have more equal opportunities to engage in paid work, showing a greater degree of gender egalitarianism in the EU labour market.

In Regressions 8 and 9 I introduce a year dummy variable for urbanisation ($URBANDPAV$) and latitude (LAT), respectively, in order to see whether the effects of urbanisation and latitude on income inequality have changed over the period 1995–2000. The effect of urbanisation and latitude is lower in 2000 (Regressions 8 and 9, respectively). The OLS (Appendix A6.3) and REs (Appendix A6.11) results show the negative correlation between urbanisation and inequality. Considering Kuznets' assumption that urbanisation is a measure of economic development, the negative relationship highlights the fact that European societies are located in the declining segment of the Kuznets curve. However, this disproves Estudillo's (1997) hypothesis that the heterogeneity of urban areas enhances, rather than lowers, inequality. Urbanisation increases perfect competition and eliminates monopoly power in the marketplaces, so that the benefits from increasing urbanisation will be a more equally distributed level of income. Highly-urbanised regions seem not only to be more economically prosperous — the correlation between income per capita and urbanisation is positive (0.46) — but also to have less inequality, as a consequence of the negative relationship between income per capita and inequality. Notably, the OLS and REs results show that the latitude variable has the 'right' sign and is significant. This result suggests that latitude may be a significant determinant of regional income performance. The northern regions exhibit the lowest income inequality levels. On the one hand, an analysis involving latitude is likely to highlight the EU north-south divide in terms of income inequality. On the other hand, bearing in mind that latitude is a good proxy for the effect of a region's climate on its level of productive efficiency, it is likely to account for a large proportion of the differences in regional inequality levels. Climate in part determines job structure and productivity. For example, tourist resorts tend to favour part-time jobs and low-skilled occupations. The demand for unqualified workers is higher in southern Europe than in central and northern Europe. In consequence, their wages are low and their employment is often precarious and part time.

Finally, the impact of the qualitative explanatory variables on income inequality (Regressions 10–12) is presented in Appendices A6.3 (OLS results) and A6.11 (REs results). The FEs estimator is not provided because there is no within-group variation in the dummy variables.

In Regression 10, 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, indeed have lower levels of income inequality than corporatist 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). In addition, 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 comes into effect mainly when the family's capacity to service its members becomes exhausted (Esping-Andersen, 1990). The 'southern' (or 'residual') welfare states have the most inegalitarian societies.

Regression 11 introduces religion as an explanatory variable. Mainly Protestant regions, which are the base category, have a lower level of income inequality than Catholic ones. Orthodox regions have the most inegalitarian societies. Finally, it is interesting to note that all categories of family structure and living arrangements affect income inequality significantly (Regression 12). Regions with a Nordic family structure have the most egalitarian societies and Southern/Catholic regions have the highest inequality.

Considering the standardised coefficients for the above regressions (Appendix A6.2),[81] women's access to work explains the largest variation in income inequality. The impact of both approaches to economic activity (work access of total population) on income inequality is high. In contrast, population ageing, unemployment and urbanisation explain only a relatively small part of the total variation in income inequality.

(b) Dynamic Model

Table 6.4 presents the long-run results for the dynamic income inequality for the whole of the population 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 whether the explanatory variables are predetermined (column b) or endogenous (column c). The short-run parameters and the specification tests (the tests regarding serial correlation and the Sargan tests)[82] are presented in Appendix A6.19.

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

[82] 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 hand, are predetermined, the specification tests are not satisfactory . The null hypothesis of no first-order autocorrelation in the differenced residuals is rejected but the null hypothesis of no second-order autocorrelation is not rejected, except for equation 6b (homoskedastic case). Additionally, the Sargan tests indicate misspecification due to the correlation between the instruments and the error term of the first-differenced equation. Finally, if the explanatory variables are assumed to be endogenous, my estimates perform well based on the specification tests. The test statistics of overidentifying restrictions do not indicate misspecification, except for equations 2c, 3c and 4c . The tests for serial correlation, once again, reject the absence of first-order serial correlation in both the homoskedastic and robust estimator of the variance-covariance matrix of the parameter estimates, but not the second-order serial correlation, except for equation 6c (homoskedastic case). Taking into account the specification tests applied to the estimated dynamic models, equation 6c (homoskedastic case), where the explanatory variables are endogenous, is the most appropriate. It is worth noting that the presence of first-order autocorrelation in the differenced residuals does not imply that the estimates are inconsistent, but the presence of second-order autocorrelation would imply that the estimates are inconsistent (Arellano and Bond, 1991).

Table 6.4: Long Run GMM: Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

	REGRESSION (1)			REGRESSION (2)			REGRESSION (3)			REGRESSION (4)		
	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
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												
OBS.	400			392			392			392		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
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)***			
OBS.	325			325			325					

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator.

Generally speaking, the exogenous, predetermined and endogenous parameters are similar to one another, denoting the robustness of the dynamic results. First, all of the equations (Appendix A6.19) reject that the lagged income inequality coefficient is zero. The coefficient on the lagged dependent variable is higher when the explanatory variables are assumed to be exogenous, except for Regression 1, and lower when the explanatory variables are endogenous, except for Regression 5. Additionally, the coefficients on the lagged dependent variable are statistically significant at the one per cent level in most equations. One finding expected was that income inequality in the current period depends on income inequality in the previous period. The rationale for this result is simple, because income inequality does not change very quickly over one year and job mobility is rather low. People do not change jobs for psychological, technological and institutional reasons (Gujarati, 2003).

Regression 1 indicates that income inequality (*IGE*1) increases in the long-run as income per capita (*IMN*) increases, thus leading to a positive correlation between the two variables. The coefficients are also statistically significant in most equations. For instance, if the strictly exogenous income is increased by one per cent, income inequality will rise by 0.0331 per cent in the long-run. This disproves the theory relating to the declining segment of the Kuznets curve, but is likely to accept Lydall's (1979) hypothesis that only a limited number of people can be transferred to higher levels of skills, while the remainder have to wait their turn. This result is consistent with the FEs conditional regressions.

The findings also indicate that income inequality in a region declines over time as the human capital variables (educational attainment (*EMN*) and educational inequality (*EGE*1)) decline, but only when they are assumed to be endogenous. According to the estimated value and assuming, for example, that human capital variables are endogenous, a one per cent increase in coefficient on educational attainment would lead in the long-run to a 0.3018 per cent increase in income inequality (Regression 2). The effects of educational attainment and educational inequality obtained after full adjustment of income inequality are positive and statistically significant only when education is endogenous (equations 2c, 3c and 4c). The combined positive impact of educational attainment and inequality on income inequality implies that, although educational expansion facilitates numerous favourable chances for individuals, the returns are higher for the rich than for the poor and rich people have more opportunities to engage in higher paid jobs. Additionally, the positive relationship between income and educational inequality highlights the responsiveness of the EU labour market to differences in qualifications and skills. Education is likely to raise the individual's marginal product in the future and therefore his/her future income (Barr, 2004: 296).

The long-run effect of the population ageing (*AGE*) variable on inequality is in most equations positive, which may reflect that with greater longevity, there will be a growing number of elderly people and since their income is lower than that of younger people, an increasing number of elderly people should lead to a rise in the number of households with a low income (Estudillo, 1997: 68), but this variable is not statistically significant. Regression 4 (equations 4a and 4b) shows that the labour force stock (*LFSTOCK*) has a positive effect on income inequality, but it is not statistically significant either. Nevertheless, the impact of the economic activity rate (*ECACRA*) has the expected sign (negative) and is statistically significant at the one per cent level (Regression 5). High unemployment (*UNEM*) is associated with higher inequality in the long-run only when unemployment is endogenous. 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 of whether changes in 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 analysis. Finally, the impact of women's access to work (*ECACRF*) on income inequality is negative and statistically significant. no matter what the explanatory variables are assumed to be.

Equation 6c is the most appropriate, taking into account the specification tests. In this equation, unemployment and female participation in the labour force are the most significant factors in 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.

6.3.1.2 Independent Educational Variable: Age at which the Highest Education Level was Completed

(a) Static Model

The p-values of Breusch and Pagan's Lagrange multiplier test and of Hausman's one favour the FEs model as the most appropriate model to determine the impact of average age at which the highest education level was completed and inequality in that age on income inequality for the population as a whole $(IGE1)$. The FEs results of the study are displayed in Table 6.5, while the OLS and REs results are presented in Appendices A6.4 and A6.12, respectively.

Table 6.5: FEs: Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMN	-0.0001 (0.0011) _(0.0013)_	-0.0003 (0.0011) _(0.0014)_	0.0006 (0.0012) _(0.0015)_	0.0020 (0.0012)* _(0.0015)_	0.0011 (0.0015) _(0.0015)_	0.0029 (0.0015)* _(0.0016)_*	0.0022 (0.0015) _(0.0016)_	0.0091 (0.0023)*** _(0.0025)_***	0.0098 (0.0019)*** _(0.0020)_***
AMN		-0.0112 (0.0044)** _(0.0044)_**	-0.0112 (0.0043)** _(0.0046)_**	-0.0093 (0.0043)** _(0.0040)_**	-0.0072 (0.0039)* _(0.0047)_	-0.0040 (0.0039) _(0.0044)_	-0.0062 (0.0039) _(0.0042)_	0.0226 (0.0094)** _(0.0109)_**	0.0087 (0.0044)* _(0.0047)_*
AGE1		1.4693 (0.3724)*** _(0.4841)_***	1.5020 (0.3705)*** _(0.4680)_***	1.4598 (0.3653)*** _(0.4410)_***	1.3965 (0.3422)*** _(0.4248)_***	1.2346 (0.3412)*** _(0.3611)_***	1.4129 (0.3448)*** _(0.3934)_***	0.5245 (0.3875) _(0.2393)_**	0.8790 (0.3311)*** _(0.3020)_***
AGE			-0.0057 (0.0023)** _(0.0024)_**	-0.0058 (0.0023)** _(0.0026)_**	-0.0080 (0.0023)*** _(0.0023)_***	-0.0053 (0.0023)** _(0.0023)_**	-0.0072 (0.0023)*** _(0.0023)_***	-0.0039 (0.0028) _(0.0025)_	-0.0016 (0.0023) _(0.0022)_
LFSTOCK				-0.3229 (0.0866)*** _(0.0935)_***					
ECACRA					-0.0104 (0.0015)*** _(0.0016)_***				
UNEM						0.5126 (0.1481)*** _(0.1591)_***		0.4417 (0.2068)** _(0.2368)_*	0.3798 (0.1446)*** _(0.1598)_**
INACTIVE							0.0902 (0.0970) _(0.1043)_		
ECACRF						-0.0075 (0.0013)*** _(0.0014)_***	-0.0085 (0.0013)*** _(0.0013)_***	-0.0036 (0.0017)** _(0.0015)_**	-0.0050 (0.0013)*** _(0.0014)_***
YR96*URBANDPAV								-0.0234 (0.0146) _(0.0155)_	
YR97*URBANDPAV								-0.0354 (0.0144)** _(0.0133)_***	
YR98*URBANDPAV								-0.0332 (0.0149)** _(0.0144)_**	
YR99*URBANDPAV								-0.0570 (0.0160)*** _(0.0161)_***	
YR00*URBANDPAV								-0.0875 (0.0180)*** _(0.0174)_***	
YR96*LAT									-0.0001 (0.0001) _(0.0001)_
YR97*LAT									-0.0004 (0.0001)*** _(0.0001)_***
YR98*LAT									-0.0004 (0.0001)*** _(0.0001)_***
YR99*LAT									-0.0007 (0.0001)*** _(0.0001)_***
YR00*LAT									-0.0010 (0.0002)*** _(0.0002)_***
CONSTANT	0.3821 (0.0121)*** _(0.0151)_***	0.5439 (0.0752)*** _(0.0751)_***	0.7922 (0.1254)*** _(0.1245)_***	0.9168 (0.1281)*** _(0.1311)_***	1.4160 (0.1394)*** _(0.1414)_***	0.9532 (0.1339)*** _(0.1324)_***	1.1178 (0.1273)*** _(0.1294)_***	0.2456 (0.2261) _(0.2558)_	0.4011 (0.1635)** _(0.1579)_**
ADJ R-SQ	0.0000	0.0380	0.0511	0.0804	0.1819	0.2024	0.1781	0.2741	0.2836
OBS.	604	534	534	534	455	455	455	299	455
LM TEST (p-value)	916.46 (0.0000)	896.69 (0.0000)	866.57 (0.0000)	730.49 (0.0000)	629.46 (0.0000)	573.75 (0.0000)	543.18 (0.0000)	338.04 (0.0000)	514.93 (0.0000)
HAUSMAN TEST (p-value)	71.46 (0.0000)	18.77 (0.0003)	19.70 (0.0006)	72.33 (0.0000)	22.33 (0.0005)	25.97 (0.0002)	19.95 (0.0028)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*)_, _(**)_ and _(***)_ denotes the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

Regression 1, which shows the unconditional and insignificant impact of income per capita (*IMN*) on income inequality has already been presented in Table 6.3. The addition of human capital variables and of population ageing (Regressions 2 and 3) does not change the estimated insignificant effect of the income per capita variable. However, adding the percentage of normally working respondents (Regression 4), the unemployment and the female economic activity rate (Regression 6), and the urbanisation level within a region (Regression 8), the impact of income per capita on income inequality is positive. Thus, the income per capita impact seems to be sensitive to the model specification and to the inclusion of different control variables. The regression results also reveal that while the relationship between the average age of respondents when the highest education level was completed (*AMN*) and income inequality is negative in Regressions 2–5, it is positive in Regressions 8 and 9, in which the urbanisation and latitude variables are included. On the one hand, the negative coefficient shows that individuals are more equal, because they face more identical opportunity sets. Earlier work experience is likely to be catalytic in the decision to increase their education to a more highly profitable level. On the other hand, the addition of the city-rural pattern variable and of the EU north-south pattern variable changes the sign of the coefficient on educational attainment. On including pattern variables, the higher the educational achievement, the higher the income inequality. The positive correlation shows that the European expansion of educational opportunity enables the poor to improve their economic circumstances by getting higher education level even if this is at an older age. Therefore, the impact of educational attainment on income inequality is not clear, because the coefficient does not keep the same sign on the inclusion of different control variables.

As expected, inequality in the age at which the highest education level was completed (*AGE*1) has a positive relationship with income inequality, highlighting the responsiveness of the EU labour market to differences in qualifications and skills. If educational achievement has a negative impact on income inequality, while educational inequality has a positive one (Regressions 2–9), education may facilitate graduate favourable chances and graduate occupational outcomes for each strata. Education offers credentials that signal underlying abilities, preferences and privileges for all individuals, but the returns on these credentials depend upon the existing socioeconomic background. The returns on highly-educated people's credentials are higher than on those of the less-educated. Both the average and inequality human capital variables play an important role in improving the absolute economic standing of people, as better-educated citizens are more productive. The results show that government expenditures on education contribute to a more equal income distribution, and that the EU labour market is responsive to differences in requirements.

The next step is to experiment with a number of alternative static specifications, adding more determinants to the equations. The impact of population ageing (*AGE*) on income inequality is negative, statistically significant and robust (Regressions 3–7). The higher the age of respondents within a region, the lower the income inequality. The introduction of access to work variables in regression analysis shows that both the percentage of normally working respondents (*LFSTOCK*) and the economic activity rate of the population (*ECACRA*) have a negative effect on inequality (Regressions 4 and 5, respectively). This point is further confirmed by the introduction of unemployment (*UNEM*) and the female participation in labour market (*ECACRF*) (Regression 6), but not by the introduction of inactivity (*UNEM*) (Regression 7) in the FEs models. The high unemployment in the EU, between 1995 and 2000 has aggravated the relative position of low-income groups contributing to higher levels of inequality. Once more, the positive relationship between unemployment and inequality confirms the fact that income received through government transfer payments, such as unemployment insurance and welfare benefits, is lower than income from wages. Regressions 8 and 9, respectively, illustrate that the effects of urbanisation (*URBANDPAV*) and latitude (*LAT*) on inequality are less pronounced in 2000 than in 1995. Moreover, according to the OLS and REs regressions, urbanisation is negatively associated with income inequality. Income inequality is higher in rural areas than in city-regions. Once again, the negative coefficient on the latitude variable demonstrates, among other things, the EU north-south divide in terms of income distribution.

Appendices A6.4 and A6.12 (Regressions 10–12) introduce the qualitative variables of religion, welfare state and family structure as explanatory ones. Orthodox regions, 'residual' (or 'southern') welfare states and Southern/Catholic living arrangement regions are the most inegalitarian societies. According to the standardised coefficients for the above regressions (Appendix A6.2), the female economic activity rate and the access to work variables explain the largest variation in income inequality. The opposite results are obtained from the standardised coefficient on population ageing.

(b) Dynamic Model

Table 6.6 shows the long-run effects of human capital distribution on income inequality ($IGE1$). The short-run coefficients and the specification tests[83] are presented in Appendix A6.20.

Regression 1 has already been presented. Nevertheless, the coefficient on the lagged income inequality variable is higher when the average education level and inequality in education level completed are added in the model rather than the average age at which the highest level of education was completed and inequality in that age are added. Considering the long-run coefficients, the impact of income per capita for the whole of the population (IMN) on income inequality is positive, but sensitive to the inclusion of control variables (as in static models) and robust to the nature of the variables (if they are exogenous, predetermined or endogenous). More specifically, the relationship is positive for Regressions 1–5. While the relationship between the average age of respondents when the highest education level was completed (AMN) and income inequality is negative in most static model specifications, this relationship is positive in dynamic ones. On the contrary, both static and dynamic equations agree with the current belief that human capital inequality ($AGE1$) has a positive relationship with income inequality and both equations are robust to model specification. On examining the impact of the additional time-variant structural variables on income inequality, most of them are statistically insignificant. More specifically, the impact of the average age of respondents (AGE), the percentage of normally working respondents ($LFSTOCK$), the percentage of unemployed respondents ($UNEM$) and the percentage of inactive respondents ($INACTIVE$) is not clear.

[83] The estimates perform well based on the specification tests, since the test statistics of serial correlation and overidentifying restrictions (the Sargan tests) in most equations do not indicate misspecification. More specifically, the Sargan tests indicate correlation between the instruments and the error term of the first-differenced equation in the equations 1b, 2b, 2c, 3b, 3c, 6b and 6c. The null hypothesis of no first-order autocorrelation in the differenced residuals is rejected, except for equations 2b, 3b, 4b, 6c (heteroskedastic case) and 4c (both homoskedastic and heteroskedastic case). There is no second-order autocorrelation in the first-differenced idiosyncratic errors in equations 5b, 5c and 6c (homoskedastic case). Hence, based on the specification tests, equation 6c (homoskedastic case) is the most appropriate.

Nevertheless, the coefficient on the economic activity rate of total population (*ECACRA*) as a proxy for work access has the 'right' sign (negative). The higher the level of work access, the more egalitarian the income distribution, as more people have the chance to increase their economic and educational opportunities. Female participation in the labour force is negatively associated with income inequality no matter what the explanatory variables are assumed to be. Finally, the coefficients on the determinants keep the same sign regardless of their nature (whether they are exogenous, predetermined or endogenous).

Table 6.6: Long Run GMM: Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

	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
IMN	0.0331 (0.0137)** _(0.0143)_**	0.0266 (0.0200) _(0.0189)_	0.0377 (0.0136)*** _(0.0151)_**	0.0248 (0.0070)*** _(0.0087)_***	0.0125 (0.0039)*** _(0.0062)_**	0.0174 (0.0067)*** _(0.0090)_*	0.0246 (0.0071)*** _(0.0088)_***	0.0131 (0.0038)*** _(0.0060)_**	0.0180 (0.0067)*** _(0.0086)_**	0.0247 (0.0081)*** _(0.0100)_**	0.0126 (0.0043)*** _(0.0065)_*	0.0162 (0.0072)** _(0.0098)_
AMN				0.0277 (0.0227) _(0.0185)_	0.0256 (0.0155)* _(0.0198)_	0.0369 (0.0208)* _(0.0204)_*	0.0314 (0.0241) _(0.0195)_	0.0261 (0.0154)* _(0.0202)_	0.0397 (0.0211)* _(0.0210)_*	0.0330 (0.0273) _(0.0225)_	0.0157 (0.0160) _(0.0208)_	0.0344 (0.0209)* _(0.0258)_
AGE1				3.6414 (1.8420)** _(2.1191)_*	6.6508 (1.4811)*** _(2.1363)_***	5.4180 (2.5306)** _(3.1632)_*	3.6686 (1.8873)* _(2.1901)_*	6.5101 (1.4654)*** _(2.0372)_***	5.0946 (2.5422)** _(2.9857)_*	3.9241 (2.1992)* _(2.5852)_	7.5766 (1.7199)*** _(2.6348)_***	7.2504 (2.4242)*** _(3.5045)_**
AGE							0.0219 (0.0157) _(0.0208)_	0.0064 (0.0065) _(0.0079)_	0.0079 (0.0072) _(0.0080)_	0.0248 (0.0189) _(0.0253)_	0.0062 (0.0071) _(0.0089)_	0.0082 (0.0080) _(0.0101)_
LFSTOCK										0.2871 (0.5805) _(0.6464)_	0.2330 (0.3822) _(0.5189)_	1.1891 (0.6860)* _(0.9369)_
ECACRA												
UNEM												
INACTIVE												
ECACRF												
OBS.	400			348			348			348		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
IMN	0.0116 (0.0070)* _(0.0064)_*	0.0028 (0.0058) _(0.0057)_	-0.0015 (0.0065) _(0.0067)_	0.0118 (0.0090) _(0.0083)_	0.0049 (0.0055) _(0.0056)_	0.0051 (0.0056) _(0.0066)_	0.0083 (0.0097) _(0.0099)_	0.0031 (0.0070) _(0.0073)_	0.0024 (0.0081) _(0.0085)_			
AMN	0.0150 (0.0148) _(0.0115)_	0.0161 (0.0145) _(0.0178)_	0.0110 (0.0169) _(0.0171)_	0.0145 (0.0189) _(0.0159)_	0.0120 (0.0152) _(0.0206)_	0.0198 (0.0162) _(0.0214)_	0.0132 (0.0194) _(0.0146)_	0.0035 (0.0163) _(0.0207)_	0.0135 (0.0203) _(0.0218)_			
AGE1	2.1284 (1.1993)* _(1.3475)_	4.1241 (1.2062)*** _(1.5829)_***	4.3813 (1.5494)*** _(2.1376)_**	2.8635 (1.6004)* _(1.8131)_	4.9000 (1.1274)*** _(1.6744)_***	5.6793 (1.2898)*** _(2.1688)_***	2.4790 (1.5943) _(1.6704)_	4.0468 (1.5011)*** _(1.6712)_**	4.4379 (1.7489)** _(1.9617)_**			
AGE	0.0157 (0.0116) _(0.0156)_	0.0081 (0.0073) _(0.0101)_	0.0059 (0.0074) _(0.0090)_	0.0172 (0.0147) _(0.0183)_	0.0069 (0.0071) _(0.0083)_	0.0033 (0.0066) _(0.0077)_	0.0214 (0.0165) _(0.0204)_	0.0100 (0.0095) _(0.0118)_	0.0104 (0.0101) _(0.0122)_			
LFSTOCK												
ECACRA	-0.0208 (0.0061)*** _(0.0077)_***	-0.0192 (0.0063)*** _(0.0083)_**	-0.0232 (0.0080)*** _(0.0099)_**									
UNEM				-1.3094 (0.9382) _(1.0707)_	-0.5564 (0.5167) _(0.8090)_	-0.6557 (0.6377) _(1.0126)_						
INACTIVE							-0.2754 (0.5540) _(0.5804)_	0.5132 (0.5460) _(0.5268)_	0.0327 (0.8473) _(0.9012)_			
ECACRF				-0.0215 (0.0083)*** _(0.0112)_*	-0.0145 (0.0055)*** _(0.0074)_*	-0.0130 (0.0058)** _(0.0077)_*	-0.0217 (0.0084)** _(0.0109)_**	-0.0220 (0.0067)*** _(0.0084)_***	-0.0206 (0.0094)** _(0.0107)_*			
OBS.	285			285			285					

Note: (*), (**) and (***) indicates significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denotes the significance of the White (1980) estimator.

6.3.2 *Income Inequality for Normally Working People*

6.3.2.1 *Independent Educational Variable: Education Level Completed*

(a) Static Model

The FEs models are the most appropriate so as to identify the determinants of income inequality for normally working people (*NGE*1) between 1995 and 2000. Table 6.7 presents the FEs regression results, while the OLS and REs results are presented in Appendices A6.5 and A6.13, respectively.

The first step in the analysis is to examine the linear impact of income per capita among normally working people (*NMN*) on the respective income inequality (Regression 1). Income per capita is positively associated with income inequality. This relationship is statistically significant and robust. This behaviour disproves the theory relating to the declining segment of the Kuznets' curve. Thus, a low percentage of workers is employed in high added-value jobs, while the remainder must wait their turn. The second step in the analysis is the introduction of educational attainment (*EMN*) and educational inequality (*EGE*1) (Regression 2). Once more, the impact of educational achievement on income inequality is not clear, as the coefficients on educational attainment are not statistically significant; while the results are consistent with the current belief that educational inequality is positively correlated with income inequality. The latter relationship is also robust. The more skewed the income distribution, the higher the population share excluded from schooling and the higher the human capital inequality (Checchi, 2000). Hence, a higher level of educational attainment through access to higher education institutions (i.e. universities) increases the occupational choices and the earning opportunities of rich people and not of the population as a whole. On the other hand, European workers who live in poverty cannot escape their condition through increased access to education, because the returns to education are greater for rich than for poor people. The positive relationship between income and educational inequality, is most probably a reflection of the responsiveness of the EU labour market to differences in qualifications and skills. The third step of analysis is the introduction of additional determinants to the equations so as to evaluate the robustness of the results. Regression 3 controls for the influence of the average age of respondents (AGE), which is not statistically significant even on adding more determinants. Regression 4 shows the negative impact of female participation in the labour force (*ECACRF*) on inequalities. The fact that income inequality among normally working people declined slightly throughout the period of study is most likely a reflection of the greater flexibility in working conditions and arrangements for women, the more adequate sharing of family responsibility and the more adequate childcare services that are now available. Both men and women seem to have more equal opportunities to engage in paid work, showing a more gender egalitarian culture in the EU labour market. Finally, Regressions 5 and 6, respectively, show that the impact of urbanisation (*URBANDPAV*) and latitude (*LAT*) on inequalities was stronger in 2000 than in 1995. Nevertheless, the OLS and REs results (Appendices A6.5 and A6.3) illustrate the ambiguous impact of urbanisation on income inequalities among normally working people, contrary to the case of income inequalities for the population as a whole. The OLS and REs coefficients on latitude are negative and statistically significant at the one per cent level. Hence the greater the latitude, the lower the income inequality among working people. As was the case with income inequality among the population as a whole, income inequality among normally working people is higher in the Mediterranean countries, where many jobs are on a part-time basis.

As expected, income inequality is lower in social-democratic welfare states, in Protestant areas and in regions with Nordic family structures. The Swedish and Danish regions offer a clear example of this pattern. Additionally, considering the standardised coefficients, educational inequality and latitude explain a large part of the variation in income inequality among normally working people (Appendix A6.2).

Table 6.7: FEs: Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)
NMN	0.0014 (0.0008)* *(0.0013)*	0.0022 (0.0011)** *(0.0015)*	0.0023 (0.0011)** *(0.0016)*	0.0020 (0.0012) *(0.0014)*	0.0074 (0.0019)*** *(0.0021)****	0.0046 (0.0014)*** *(0.0016)****
EMN		0.0347 (0.0304) *(0.0292)*	0.0349 (0.0304) *(0.0293)*	0.0322 (0.0295) *(0.0254)*	-0.0055 (0.0419) *(0.0330)*	0.0250 (0.0325) *(0.0268)*
EGE1		0.0545 (0.0233)** *(0.0169)****	0.0546 (0.0233)** *(0.0169)****	0.0326 (0.0220) *(0.0147)***	0.0596 (0.0319)* *(0.0219)****	0.0377 (0.0221)* *(0.0146)***
AGE			-0.0006 (0.0022) *(0.0020)*	-0.0017 (0.0021) *(0.0019)*	-0.0011 (0.0028) *(0.0024)*	0.0000 (0.0023) *(0.0019)*
ECACRF				-0.0035 (0.0012)*** *(0.0011)****	-0.0012 (0.0018) *(0.0016)*	-0.0020 (0.0013) *(0.0013)*
YR96*URBANDPAV					-0.0101 (0.0155) *(0.0134)*	
YR97*URBANDPAV					-0.0316 (0.0156)** *(0.0145)***	
YR98*URBANDPAV					0.0126 (0.0171) *(0.0157)*	
YR99*URBANDPAV					-0.0129 (0.0180) *(0.0168)*	
YR00*URBANDPAV					-0.0570 (0.0188)*** *(0.0167)****	
YR96*LAT						0.0000 (0.0001) *(0.0001)*
YR97*LAT						-0.0002 (0.0001) *(0.0001)**
YR98*LAT						0.0000 (0.0001) *(0.0001)*
YR99*LAT						-0.0002 (0.0001) *(0.0001)**
YR00*LAT						-0.0004 (0.0001)*** *(0.0001)****
CONSTANT	0.2019 (0.0127)*** *(0.0186)****	0.1231 (0.0390)*** *(0.0328)****	0.1486 (0.1035) *(0.0878)**	0.3855 (0.1096)*** *(0.0841)****	0.1991 (0.1658) *(0.1255)*	0.2071 (0.1320) *(0.1040)***
ADJ R-SQ	0.0057	0.0207	0.0209	0.0337	0.1556	0.0682
OBS.	604	596	596	513	299	513
LM TEST (p-value)	676.24 (0.0000)	555.86 (0.0000)	555.66 (0.0000)	557.12 (0.0000)	259.68 (0.0000)	538.47 (0.0000)
HAUSMAN TEST (p-value)	38.07 (0.0000)	34.03 (0.0000)	34.36 (0.0000)	14.72 (0.0116)		

Note: (*), (**) and (***) indicates significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denotes the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

(b) Dynamic Model

Table 6.8 displays the long-run results for the income inequality for normally working people (*NGE*1) equations. The validity of the models is confirmed by the test results[84] reported in Appendix A6.21, which also presents the short-run results.

As expected, all the equations (in Appendix A6.21) reject that the lagged income inequality for working people parameter is zero, because a few workers change job within one year. Most people did the same job throughout the whole period of study for psychological, technological and institutional reasons. Analysing the long-run coefficients on the determinants of income variations of normally working people (Table 6.8), Regression 1 shows that income per capita (NMN), once again, positively affects income inequality, but that impact is sensitive to the model specification in terms of the assumption of the determinants (whether they are exogenous, predetermined or endogenous). Only a limited number of people can transfer from the low levels of skill to higher ones so as to get higher rewards. The results also indicate that the long-run impact of human capital distribution on income inequality is not clear. Neither educational attainment (*EMN*) nor educational inequality (*EGE*1) are statistically significant, except for educational inequality in equation 2b, where the explanatory variables are assumed to be predetermined. In this case, the higher the educational inequality, the higher the income inequality. Since both income and human capital inequalities have decreased slightly between 1995 and 2000, a more equal education may have achieved greater equality in economic opportunities and incomes, without challenging the European institutions and without requiring any major redistribution of capital. Regression 3 shows that the average age of respondents (*AGE*) has an ambiguous effect on income inequality, while Regression 4 displays the negative and significant relationship between female participation in labour force (*ECACRF*) and the distribution of income among normally working people.

[84] The estimates perform well based on the specification tests. The Sargan tests do not reject the overidentifying restrictions, except for equations 2c and 3c. The tests for serial correlation reject the absence of first-order in all equations. The null hypothesis of no second-order autocorrelation in the differenced residuals is rejected in equations 1a, 1b, 2a, 2c, 3a, 3b, 3c (homoskedastic case) and 2b (both homoskedastic and heteroskedastic case). Based on specification tests, equations 1a, 1b, 2a, 3a, 3b (homoskedastic case) and 2b (both homoskedastic and heteroskedastic case) are the most appropriate models.

Table 6.8: Long Run GMM: Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

	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
NMN	0.0186 (0.0107)* *(0.0118)*	-0.0408 (0.0530) *(0.0650)*	-0.1397 (0.2707) *(0.3017)*	0.0277 (0.0301) *(0.0338)*	0.0125 (0.0064)* *(0.0077)*	0.0123 (0.0088) *(0.0098)*	0.0256 (0.0293) *(0.0336)*	0.0126 (0.0065)* *(0.0078)*	0.0136 (0.0086) *(0.0096)*	0.0066 (0.0080) *(0.0079)*	0.0083 (0.0058) *(0.0057)*	0.0052 (0.0076) *(0.0073)*
EMN				-0.3854 (0.6791) *(0.7199)*	0.1074 (0.1253) *(0.1346)*	0.2195 (0.1791) *(0.1865)*	-0.4239 (0.7223) *(0.7517)*	0.1031 (0.1249) *(0.1355)*	0.2153 (0.1745) *(0.1786)*	-0.0583 (0.1520) *(0.1689)*	0.0116 (0.0913) *(0.1077)*	0.0443 (0.1355) *(0.1522)*
EGE1				-0.2789 (0.4984) *(0.4951)*	0.1138 (0.0823) *(0.0671)**	0.1118 (0.1202) *(0.1136)*	-0.3477 (0.5684) *(0.5574)*	0.1028 (0.0839) *(0.0673)*	0.1007 (0.1184) *(0.1074)*	-0.0854 (0.1114) *(0.1153)*	-0.0269 (0.0687) *(0.0699)*	-0.0259 (0.1066) *(0.1087)*
AGE							0.0487 (0.0651) *(0.0649)*	0.0095 (0.0106) *(0.0106)*	0.0113 (0.0111) *(0.0131)*	0.0274 (0.0171) *(0.0203)*	0.0151 (0.0093) *(0.0096)*	0.0229 (0.0135)* *(0.0131)**
ECACRF										-0.0232 (0.0091)** *(0.0127)**	-0.0159 (0.0052)*** *(0.0062)***	-0.0145 (0.0082)* *(0.0094)*
OBS.	400			392			392			325		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator.

6.3.2.2 Independent Educational Variable: Age at which the Highest Education Level was Completed

(a) Static Model

The validity of the static models which explore the impact of average age at which the highest education level was completed and inequality in that age on income inequality for normally working people (*NGE*1) is confirmed by the test results presented in Table 6.9. Once more, the FEs models are the most appropriate. The OLS and REs results are displayed in Appendices A6.6 and A6.14, respectively.

The unconditional impact of the income per capita of normally working people (*NMN*) on the respective income inequality is positive and statistically significant at the ten per cent level, but only when disturbances are assumed to be homoskedastic. The addition of more determinants changes the estimated effect of income per capita, as the conditional impact of average income is statistically insignificant in Regressions 2–4, but statistically significant at the one per cent level in Regressions 5–6. Thus, the relationship between income per capita and income inequality is positive, but sensitive to the model specification. The positive impact of income per capita on income inequality is robust only when the proxy for human capital is the education level completed.

Regression 2 displays the estimated effect of human capital variables on inequality. On the one hand, the impact of the average age at which the highest education level was completed (*AMN*) is positive and statistically significant only when the variables for population ageing, women's access to work and latitude are introduced into the model (Regression 6). Thus controlling for the above factors, the increasing proportion of the European population who attain education at an older age does not lead to inflation in the value of educational credentials, which, in turn, leads to a decrease in the salaries of highly-educated workers. Some of them have work experience and they are very realistic about their decisions. Educational attainment at an older age improves specific and general information about labour market institutions. However, improved information about the job market reduces the probable divergence between anticipated and actual returns to education (Rosen, 1994). On the other hand, the inequality in the age at which the highest education level was completed (*AGE*1) is positively associated with income inequality for normally working people. The higher the human capital inequality, the higher the income inequality. Although education opens up numerous favourable opportunities to individuals, those opportunities are greater for highly-educated workers than for less-educated workers. Increasing the educational preferences raises the individuals' occupational outcomes according to their current economic status. In other words, the positive relationship between income and human capital inequality is likely to underscore the responsiveness of the EU labour market to differences in qualifications and skills.

The impact of population ageing (*AGE*) on income inequality is insignificant (Regressions 3–6). Female participation in labour force (*ECACRF*) is negatively associated with income inequality. Although there are still differences in the opportunities open to men and women to engage in paid work, those differences appear to have declined between 1995 and 2000. The reduction in the causes of gender equality in the EU labour market is likely to have led to a decrease the observed income inequality throughout the period of study. For instance, many men have more responsibilities as caregivers and in household tasks in 2000 than they did in 1995. Regressions 5 and 6 show, once more, that the impact of urbanisation (*URBANDPAV*) and latitude (*LAT*) on income inequality is less in 2000 than in 1995. The OLS and REs results (Appendices A6.6 and A6.14) show that the relationship between urbanisation and inequality is unclear, while northern regions have lower levels of income inequality than southern areas.

In Regressions 7, 8 and 9 of Appendices A6.6, for the OLS results, and A6.14, for the FEs results, welfare state, religion and family structure dummies are added to the regressions. The addition of these dummies shows that income inequality is lower in social-democratic welfare states, in mainly Protestant regions and in regions with a small household size. Finally, the standardised coefficients demonstrate that educational achievement explains a major part of the variation in income inequality for normally working people (Appendix A6.2).

Table 6.9: FEs: Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)
NMN	0.0014 (0.0008)* _(0.0013)_	0.0009 (0.0009) _(0.0013)_	0.0009 (0.0009) _(0.0014)_	0.0011 (0.0011) _(0.0014)_	0.0059 (0.0017)*** _(0.0018)_***	0.0042 (0.0014)*** _(0.0016)_**
AMN		-0.0013 (0.0044) _(0.0039)_	-0.0013 (0.0044) _(0.0039)_	0.0023 (0.0039) _(0.0037)_	0.0109 (0.0100) _(0.0123)_	0.0098 (0.0047)** _(0.0043)_**
AGE1		0.9458 (0.3805)** _(0.4328)_**	0.9471 (0.3812)** _(0.4311)_**	0.7779 (0.3452)** _(0.3349)_**	0.6347 (0.4101) _(0.2761)_**	0.5221 (0.3464) _(0.2855)_*
AGE			-0.0002 (0.0024) _(0.0021)_	-0.0011 (0.0022) _(0.0019)_	0.0012 (0.0029) _(0.0025)_	0.0016 (0.0024) _(0.0019)_
ECACRF				-0.0044 (0.0013)*** _(0.0012)_***	-0.0019 (0.0018) _(0.0015)_	-0.0029 (0.0014)** _(0.0014)_**
YR96*URBANDPAV					-0.0037 (0.0153) _(0.0132)_	
YR97*URBANDPAV					-0.0213 (0.0152) _(0.0132)_	
YR98*URBANDPAV					-0.0057 (0.0155) _(0.0137)_	
YR99*URBANDPAV					-0.0314 (0.0164)* _(0.0145)_**	
YR00*URBANDPAV					-0.0678 (0.0183)*** _(0.0166)_***	
YR96*LAT						0.0000 (0.0001) _(0.0001)_
YR97*LAT						-0.0001 (0.0001) _(0.0001)_
YR98*LAT						-0.0001 (0.0001) _(0.0001)_
YR99*LAT						-0.0003 (0.0001)** _(0.0001)_**
YR00*LAT						-0.0006 (0.0002)*** _(0.0002)_***
CONSTANT	0.2019 (0.0127)*** _(0.0186)_***	0.2034 (0.0769)*** _(0.0702)_***	0.2136 (0.1277)* _(0.1132)_*	0.3886 (0.1215)*** _(0.1088)_***	-0.0169 (0.2381) _(0.2878)_	0.0333 (0.1688) _(0.1466)_
ADJ R-SQ	0.0057	0.0184	0.0184	0.0485	0.1506	0.0885
OBS.	604	534	534	455	299	455
LM TEST (p-value)	676.24 (0.0000)	502.19 (0.0000)	491.51 (0.0000)	428.00 (0.0000)	221.96 (0.0000)	388.29 (0.0000)
HAUSMAN TEST (p-value)	38.07 (0.0000)	9.93 (0.0192)	10.37 (0.0332)	16.94 (0.0046)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*)_, _(**)_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

(b) Dynamic Model

Table 6.10 displays the long-run effects of the distribution of human capital, as measured by the age at which the highest education level was completed, on income inequality for normally working people ($NGE1$). The specification tests[85] which were applied to the dynamic models and the short-run effects are reported in Appendix A6.22. It also shows the expected positive and statistically significant effect of the lagged income inequality on the current inequality.

Regressions 1–4 show the unconditional and conditional impact of income per capita of normally working people (*NMN*) on the respective income inequality. Income per capita is positively associated with income inequality only when the determinants are assumed to be strictly exogenous. The next step in the dynamic analysis is the introduction of human capital distribution as measured by the average age at which the highest education level was completed (*AMN*) and by inequality in the respective age ($AGE1$). The long-run impact of human capital stock on inequality is ambiguous in most equations. The effect of this proxy for human capital inequality on income inequality is positive, but statistically significant only when the determinants are assumed to be predetermined. Regression 4 shows that population ageing (*AGE*) has a positive effect on inequality, while the same regression illustrates the negative sign of the coefficient for female participation in the labour force. As expected, the greater the access of women to work ($ECACRF$), the lower the income inequality for normally working people.

[85] The Sargan tests do not reject the overidentifying restrictions in all equations. The tests for serial correlation reject the absence of first-order in all equations. The null hypothesis of no second-order autocorrelation in the differenced residuals is rejected in all homoskedastic cases expept for equations 1c and 4a. Based on specification tests, all homoskedastic equations except for equations 1c and 4a are the most appropriate models.

Table 6.10: Long Run GMM: Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

	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
NMN	0.0186 (0.0107)* *(0.0118)*	-0.0408 (0.0530) *(0.0650)*	-0.1397 (0.2707) *(0.3017)*	0.0150 (0.0064)** *(0.0074)***	0.0028 (0.0044) *(0.0049)*	0.0019 (0.0080) *(0.0087)*	0.0140 (0.0063)** *(0.0073)**	0.0034 (0.0041) *(0.0046)*	0.0019 (0.0079) *(0.0083)*	0.0049 (0.0050) *(0.0045)*	-0.0026 (0.0035) *(0.0038)*	-0.0043 (0.0039) *(0.0042)*
AMN				0.0278 (0.0263) *(0.0234)*	0.0387 (0.0247) *(0.0307)*	0.0547 (0.0377) *(0.0450)*	0.0348 (0.0275) *(0.0236)*	0.0347 (0.0223) *(0.0290)*	0.0549 (0.0375) *(0.0458)*	0.0236 (0.0154) *(0.0139)**	0.0191 (0.0140) *(0.0183)*	0.0208 (0.0166) *(0.0195)*
AGE1				2.1955 (1.9126) *(1.8640)*	5.1657 (2.1666)** *(2.3763)***	4.6384 (3.6902) *(2.9056)*	1.8811 (1.9277) *(1.9190)*	5.3301 (2.0089)*** *(2.3419)***	4.1944 (3.7648) *(2.9322)*	0.3161 (1.2229) *(1.0294)*	2.5583 (1.1660)** *(1.2633)***	2.3469 (1.6795) *(1.6403)*
AGE							0.0162 (0.0151) *(0.0159)*	0.0083 (0.0089) *(0.0088)*	0.0113 (0.0119) *(0.0119)*	0.0185 (0.0106)* *(0.0135)*	0.0115 (0.0070)* *(0.0087)*	0.0104 (0.0078) *(0.0083)*
ECACRF										-0.0164 (0.0052)*** *(0.0060)****	-0.0156 (0.0052)*** *(0.0057)****	-0.0183 (0.0062)*** *(0.0070)***
OBS.	400			348			348			285		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator.

6.3.3 Conclusion

Table 6.11 displays the sign of the income per capita, educational attainment and educational inequality coefficients and the robustness of the results in income inequality (both for the whole of the population and for normally working people) model specifications (both the FEs models and the long-run GMM models). Considering the income distribution either for the population as a whole or for normally working people, the results are approximately the same (partial conclusion (1) versus partial conclusion (2)). Taking into account the specification tests applied to the estimated static and dynamic 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, refuting the theory that places it in the declining segment of the Kuznets curve. The results are also likely to concur with Lydall's (1979) hypothesis that only a limited number of people can be transferred to higher levels of skills and income, while the reminder have to wait their turn. Moreover, regional economic development seems not to increase the occupational choices and the earning opportunities of the population as a whole, but rather only those of rich people. While the impact of *educational attainment* on income inequality is not clear, *educational inequality* is associated with higher income inequality. It is human capital inequality that seems to matter. It is worth noting that the coefficients on educational inequality (both inequality in the education level completed and inequality in the age at which the highest education level was completed) are higher when the dependent variable is income inequality among the population as a whole rather than income inequality for normally working people. Moreover, the adjusted R-squared of the equations that include income inequality among the population as a whole are higher than that of the equations relating to normally working people. It is likely to depict that equations with income inequality for everyone indicates better FEs models in terms of a good fit.

Taking into account *urbanisation*, the increasing weight of the urban relative to the rural population means that income inequality among the population as a whole is decreasing (OLS and REs results). In contrast, the impact of urbanisation on income inequality among normally working people is not clear. Hence, the impact of urbanisation on income inequality is sensitive to the definition of income distribution. Additionally, considering the *latitude* variable, the results show that income inequality (both for the population as a whole and for normally working people) is lower in the north than in the south. Finally, considering *institutions*, the results show that the social-democratic welfare states, the mainly Protestant regions and those with Nordic family structures are among the most egalitarian. Thus, the detected patterns of ESDA have undergone preliminary tests in the static regression models.

Autoregressive models (short-run GMM regressions) highlight the persistence of income inequality, because income distribution does not change rapidly. Since the estimated coefficient on the lagged dependent variable is high and significant for all the dynamic specifications, the estimated long-run coefficients on the explanatory variables are less efficient and biased.

The 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 a higher quality of education and increasing educational attainment in general may have not any effect on income inequality. They also indicate that income and human capital inequality are connected, highlighting the responsiveness of the EU labour market to differences in qualifications and skills. Since both income and human capital inequalities have decreased slightly between 1995 and 2000, a more equal distribution of education may have helped towards a greater level of equality in economic opportunities and incomes, without challenging the European institutions and without requiring any major redistribution of capital. Better-educated people earn more than less-educated people. An individual who acquires more education is likely to become more productive. Microeconomic changes in human capital distribution as measured by inequality levels seem to be more important than those measured by average levels.

Table 6.11: Determinants of Income Inequality

	dependent variable										
	income inequality for all people					**income inequality for normally working people**					**general conclusion**
independent variables	education level completed		age at which the highest education level was completed		**partial conclusion (1)**	education level completed		age at which the highest education level was completed		**partial conclusion (2)**	
	static	dynamic	static	dynamic		static	dynamic	static	dynamic		
income per capita	+ (rob)	+ (rob)	+ (non rob)	+ (non rob)	+ (non rob)	+ (rob)	+ (non rob)	+ (non rob)	+ (non rob)	+ (non rob)	+ (non rob)
educational attainmnet	not clear	+ (non rob)	not clear	+ (non rob)	not clear	not clear	not clear	+ (non rob)	+ (non rob)	not clear	not clear
educational inequality	+ (rob)	+ (non rob)	+ (rob)	+ (rob)	+ (non rob)	+ (rob)	+ (non rob)	+ (rob)	+ (non rob)	+ (non rob)	+ (non rob)

Note: 'not clear' means either not statistically significant coefficients in all equations or coefficients do not keep the same sign; 'robustness' means sensitivity of coefficients in terms of additional explanatory variables.

6.4 Regression Results for Educational Inequality

This section explores the determinants of educational inequality with both static and dynamic analysis.

$$EducIneq_{it} = \beta_1' EducAtt_{it} + \beta_2' Incpc_{it} + \beta_3' IncIneq_{it} + \beta_4' x_{it} + u_{it}$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...,6$).[86] $EducIneq_{it}$ is educational inequality, $EducAtt_{it}$ is educational attainment, $Incpc_{it}$ is income per capita, $IncIneq_{it}$ is income inequality, x_{it} is a vector of control variables (Table 6.2), $\beta_{1,...,4}$ are coefficients and u_{it} is the composite error.

Following the rationale of income inequality regressions, in Table 6.12–Table 6.19 Regression 1 shows the linear impact of educational attainment on educational inequality. Regression 2 shows the introduction of income distribution as measured by income per capita and income inequality. Regression 3 tests for the influence of population ageing. Regressions 4 and 5 show the impact of proxies for access to work on educational inequality. In Regressions 6 and 7 controls for unemployment and inactivity as well as a control for women's access to work are included in the static and dynamic models. The

[86] $t = 1$ denotes 1995,..., $t = 6$ denotes 2000.

next step in the static analysis is the introduction of quantitative and qualitative time-invariant variables. Regressions 8 and 9 run a preliminary test for the urban-rural and the EU north-south patterns, respectively. Finally, welfare state, religion and family structure dummies are added in Regressions 10, 11 and 12, respectively.

The first subsection explores the determinants of inequality in the education level completed, while the second explores the determinants of inequality in the age at which the highest education level was completed.

6.4.1 Inequality in Education Level Completed

6.4.1.1 Independent Income Variable: Income of the Population as a Whole

(a) Static Model

The OLS, FEs and REs models of inequality in the education level completed ($EGE1$), when the explanatory variable is income distribution for the population as a whole, are estimated and appropriate tests are used. The statistical evidence is in favour of the FEs models, which are presented in Table 6.12. Appendices A6.7 and A6.15 display the OLS and REs models, respectively.

Table 6.12: FEs: Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EMN	-1.0761 (0.0251)*** (0.0225)***	-1.0985 (0.0325)*** (0.0376)***	-1.0976 (0.0326)*** (0.0375)***	-1.0913 (0.0333)*** (0.0373)***	-1.1416 (0.0366)*** (0.0443)***	-1.1385 (0.0371)*** (0.0445)***	-1.1389 (0.0375)*** (0.0437)***	-0.8831 (0.0618)*** (0.0477)***	-1.1879 (0.0435)*** (0.0561)***
IMN		0.0038 (0.0027) (0.0024)	0.0033 (0.0028) (0.0025)	0.0037 (0.0028) (0.0026)	0.0051 (0.0036) (0.0031)*	0.0055 (0.0037) (0.0030)*	0.0053 (0.0037) (0.0031)*	0.0011 (0.0055) (0.0058)	0.0008 (0.0046) (0.0038)
IGE1		0.2725 (0.0867)*** (0.0786)***	0.2793 (0.0873)*** (0.0811)***	0.2669 (0.0884)*** (0.0810)***	0.1499 (0.1073) (0.0888)*	0.1674 (0.1106) (0.0868)*	0.1769 (0.1086) (0.0865)**	0.3792 (0.1377)*** (0.1113)***	0.2306 (0.1148)** (0.0862)***
AGE			0.0030 (0.0043) (0.0040)	0.0028 (0.0043) (0.0040)	0.0031 (0.0048) (0.0047)	0.0047 (0.0049) (0.0048)	0.0041 (0.0049) (0.0052)	0.0126 (0.0059)** (0.0051)**	0.0002 (0.0051) (0.0048)
LFSTOCK				-0.1518 (0.1668) (0.1389)					
ECACRA					-0.0101 (0.0032)*** (0.0033)***				
UNEM						0.1448 (0.3222) (0.2614)		0.2673 (0.4462) (0.4685)	0.3434 (0.3238) (0.2801)
INACTIVE							0.0354 (0.2066) (0.2098)		
ECACRF						-0.0058 (0.0028)** (0.0028)**	-0.0060 (0.0028)** (0.0026)**	-0.0090 (0.0036)** (0.0037)**	-0.0083 (0.0029)*** (0.0030)***
YR96*URBANDPAV								-0.0041 (0.0318) (0.0449)	
YR97*URBANDPAV								-0.0056 (0.0326) (0.0394)	
YR98*URBANDPAV								-0.0787 (0.0345)** (0.0372)**	
YR99*URBANDPAV								-0.0736 (0.0371)** (0.0415)*	
YR00*URBANDPAV								-0.0885 (0.0403)** (0.0487)*	
YR96*LAT									-0.0001 (0.0003) (0.0003)
YR97*LAT									0.0001 (0.0003) (0.0002)
YR98*LAT									0.0003 (0.0003) (0.0002)
YR99*LAT									0.0009 (0.0003)*** (0.0003)***
YR00*LAT									0.0006 (0.0003)* (0.0003)*
CONSTANT	1.5964 (0.0189)*** (0.0176)***	1.4659 (0.0415)*** (0.0315)***	1.3335 (0.1959)*** (0.1842)***	1.4187 (0.2171)*** (0.2171)***	1.9332 (0.3052)*** (0.2898)***	1.5403 (0.2746)*** (0.2647)***	1.5688 (0.2670)*** (0.2274)***	1.1844 (0.3466)*** (0.3073)***	1.9025 (0.2923)*** (0.2845)***
ADJ R-SQ	0.7888	0.7940	0.7942	0.7945	0.7623	0.7596	0.7595	0.8377	0.7696
OBS.	596	596	596	596	513	513	513	299	513
LM TEST (p-value)	1134.37 (0.0000)	1047.57 (0.0000)	1066.42 (0.0000)	942.76 (0.0000)	780.79 (0.0000)	784.54 (0.0000)	781.83 (0.0000)	477.54 (0.0000)	798.16 (0.0000)
HAUSMAN TEST (p-value)	23.91 (0.0000)	79.28 (0.0000)	166.81 (0.0000)	99.03 (0.0000)	523.31 (0.0000)	69.25 (0.0000)	37.63 (0.0000)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

Regression 1 examines the pure educational attainment (*EMN*) effect on educational inequality. There is a strong negative relationship between average level of education attainment and inequality in the education level completed. The coefficient on educational attainment is statistically significant at the one per cent level. The R-squared is 0.7888. It shows that educational attainment explains a large variation in educational inequality in the sample. In terms of the goodness-of-fit, it is likely to indicate a good unconditioned model. Including the other elements of the model does not change this result. Educational attainment plays a prominent role and appears robust to the inclusion of additional influences. Education seems to be one of the most powerful instruments known for reducing educational inequality. One reason for this may be that the increased opportunities to acquire higher education enable more people to improve their socioeconomic circumstances. Another reason may be that educational expansion and free primary and secondary education have offered educational opportunities and numerous favourable chances to both advantaged and disadvantaged groups. The latter enjoy more favourable opportunities than the former. The negative connection between educational achievement and educational inequality also highlights egalitarianism, because the members of society become better off at a different speed. Individuals are more equal if they face more identical educational opportunity sets.

The income per capita of the population as a whole (*IMN*) and income inequality among the whole of the population (*IGE*1) variables, which are both indicators of income distribution, are added to the model (Regression 2). The impact of income per capita on educational inequality is positive, but it is not statistically significant in Regressions 2–4 and 8–9. This impact is positive and statistically significant at the ten per cent level in Regressions 5–7 for the heteroskedastic error term. The findings indicate the sensitivity of the regression results to various specifications of the FEs models and to the inclusion of different control variables. This outcome could indicate that an increase in the income per capita of a region raises the educational opportunities of the highest strata, which implies greater educational inequality. In brief, the positive income per capita–educational inequality relationship is contrary to Saint-Paul and Verdier's (1993) hypothesis that the higher the income levels of the rich (as a result of the high income per capita of the population as a whole), the higher the rate of taxation, the greater the expenditure on public education programmes, the higher the public investment in human capital and, therefore, the greater the educational opportunities of the lowest strata. Although public education programmes constitute the major portion of European education programmes, they are not sufficiently effective to lessen the inequality in education level completed. The coefficients on income inequality, on the other hand, are significant, have the expected sign and are fairly constant throughout the different specifications. The greater the income inequality, the greater the human capital inequality. The most likely explanation is that rich people have higher educational opportunities than the poor. However, the most highly regarded institutions provide higher human capital returns. Rich people have better job chances and greater opportunities to take their education to an otherwise more profitable level, should it be necessary. Additionally, a further increase in income inequality may lead to a self-perpetuating poverty trap that may in turn increase the population share excluded from schooling. Due to the causality effects, the positive impact of income inequality on educational inequality is likely to be reflected in the responsiveness of the EU labour market to differences in qualifications and skills.

The next step in the regression analysis is to examine the robustness of the empirical results by adding a number of other determinants in Regression 2. The impact of these additional factors is also examined. Regression 3 tests for the influence of population ageing (AGE). The impact of the average age of respondents on human capital inequality seems to be ambiguous, because it is statistically significant in Regression 8 only. This regression shows that an increase in the number of elderly and probably retired people leads to a rise in human capital inequality. This finding refutes Motonishi's (2006) argument that as people get older, they have a lack of educational opportunities. A somewhat different view has been put forward by Dur et al. (2004) who stress that the mature working age cohort do not face credit constraints that prevent them from taking up studies at the higher education level. The percentage of normally working respondents $(LFSTOCK)$ has no clear effect (Regression 4). However, the coefficient for the economic activity rate of the population as a whole (*ECACRA*) is significant at the one per cent level and has the expected sign. The greater the access to work, the lower the educational inequality (Regression 5). Greater regional access to work (either full-time work or atypical employment) implies higher regional earnings which, in turn, increase the possibility of entering higher education. Although people with lower skills are being relegated to these forms of employment and condemned to lower salaries (Rodríguez-Pose, 2002), they have the opportunity to supplement their education level in order to improve their socioeconomic status. The coefficients on unemployment (*UNEM*) and inactivity (*INACTIVE*) are not statistically significant (Regressions 6 and 7, respectively). These variables cannot account for the variation in the regional human capital inequality level. On the other hand, Regressions 6–9 show a negative connection between women's access to work (*ECACRF*) and educational inequality. It supports the view that increasing women's access to the labour market — through more adequate childcare services, more flexible working conditions and more sharing of family responsibilities — implies greater opportunities to engage in paid work.

In Regressions 8 and 9 I introduce a year dummy variable for urbanisation (*URBANDPAV*) and latitude (*LAT*), respectively, in order to see whether the effects of urbanisation and latitude have changed over the period 1995–2000. The effect of urbanisation was lower in 2000, while the effect of latitude is higher in 1999. The OLS and REs results of these regressions (Appendices A6.7 and A6.15) test for the EU urban-rural and EU north-south patterns. The coefficient on urbanisation is positive, but the coefficient on latitude is negative.

Due to the high value of the adjusted R-squared in all the specification FEs models, a significant proportion of cross-regional and over time variations in inequality in the education level completed have already been explained.

Regressions 10 and 11 (Appendices A6.7 and A6.15) show that human capital inequality is higher in liberal welfare states and in Anglican areas such as the United Kingdom. Regression 12 shows that educational inequality is lower in Nordic family structures. Finally, taking into account the standardised coefficients (Appendix A6.2), educational attainment accounts for a major part of the variation in educational inequality.

(b) Dynamic Model

Table 6.13 displays the long-run results for the GMM estimation of the dynamic educational inequality (*EGE*I) model. The short-run evolution of the determinants of educational inequality in the EU and the test statistics for serial correlation and overidentifying restriction[87] are presented in Appendix A6.23.

The coefficient on the lagged dependent variable lies in the interval between 0.2049 (equation 7c) and 0.5335 (equation 1a) (Appendix A6.23). It is higher when the explanatory variables are assumed to be exogenous, except for Regression 5. Additionally, the coefficients on lagged educational inequality are statistically significant at least at the five per cent level in both homoskedastic and robust cases. One would expect to find that educational inequality in the current period depends on educational inequality in the lagged one-year period. However, most people in the survey (older people) have already completed their formal studies and thus their time-series variation in education level completed is zero. People who have not completed their studies (like young people) change education level at least every three years (i.e. from the first stage to the second stage of secondary education level completed).

The long-run effect of educational attainment (EMN), which is obtained after full adjustment of educational inequality, is negative, robust and statistically significant at the one per cent level (Regressions 1–7). The higher the educational attainment, the lower the educational inequality. This finding is consistent with the static results. Regression 2 displays the introduction of income distribution as measured by income per capita (IMN) and income inequality ($IGE1$). This regression indicates that regional economic development has a negative influence on human capital inequality. The negative relationship seems to concur with the Saint-Paul and Verdier (1993) hypothesis. However, this outcome is sensitive to the econometric specifications. For instance, the coefficients on income per capita are not statistically significant in Regressions 5–7. Additionally, the income per capita coefficient is fairly constant through the different and statistically significant specifications. I therefore find some evidence that both educational attainment and income per capita alleviate the inequality in human capital. As in the static models, the results also show that a more unequal distribution of income is associated with higher

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[87] In all equations, the Sargan tests reject the overidentifying restrictions, because they indicate correlation between the instruments and the error term. The tests regarding serial correlation reject the absence of first-order in all equations. The tests of second-order are rejected in heteroskedastic equations 3b, 5a, 7a and 7b. Based on the specification tests, the heteroskedastic equations 3b, 5a, 7a and 7b are the most appropriate.

educational inequality. The coefficient on income inequality is significant and does not disappear when other background factors are held constant.

The long-run impact of population ageing (*AGE*) on educational inequality is positive. However, there is a significant coefficient on the ageing variable in 6 out of 15 equations. In Regressions 4 and 5, I include work access controls. While the impact of the percentage of normally working respondents (*LFSTOCK*) is not clear, that of the economic activity rate of total population (*ECACRA*) is negative and statistically significant, no matter what the explanatory variables are assumed to be. Regression 6 shows that the impact of unemployment (*UNEM*) on educational inequality is not clear, as in the respective FEs model. Although the OLS, FEs and REs coefficients on inactivity (*INACTIVE*) are not statistically significant, the long-run GMM results (Regression 7) show that the predetermined and endogenous impact of the percentage of inactive respondents on educational inequality is negative and statistically significant. The higher the percentage of inactive young people, the lower the educational inequality in the long run, because more widespread access to education means that young people are kept out of the labour market, as reflected in the high incidence of youth inactivity (Rodríguez-Pose 2002). Finally, Regressions 6 and 7 show a negative connection between women's access to work (*ECACRF*) and educational inequality.

It is remarkable that apart from income per capita, regressors have been found to be robust, in the sense that their estimated parameters keep the same sign and are statistically significant in both static and dynamic specifications. Additionally, the coefficients on educational attainment and income inequality are not sensitive in the inclusion of different control variables.

Table 6.13: Long Run GMM: Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

	REGRESSION (1)			REGRESSION (2)			REGRESSION (3)			REGRESSION (4)		
	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
EMN	-1.1667 (0.0982)*** (0.1254)***	-1.3155 (0.1363)*** (0.2353)***	-1.7170 (0.2330)*** (0.4263)***	-1.3328 (0.1201)*** (0.1691)***	-1.3964 (0.1207)*** (0.1632)***	-1.4555 (0.1397)*** (0.1831)***	-1.2518 (0.1175)*** (0.1616)***	-1.3231 (0.1200)*** (0.1454)***	-1.4251 (0.1430)*** (0.1719)***	-1.2364 (0.1167)*** (0.1628)***	-1.3261 (0.1248)*** (0.1407)***	-1.4413 (0.1421)*** (0.1577)***
IMN				0.0050 (0.0127) (0.0099)	-0.0292 (0.0141)** (0.0133)**	-0.0346 (0.0195)* (0.0235)	-0.0008 (0.0124) (0.0093)	-0.0343 (0.0138)** (0.0143)**	-0.0355 (0.0194)* (0.0234)	0.0027 (0.0128) (0.0092)	-0.0408 (0.0155)*** (0.0150)***	-0.0315 (0.0206) (0.0193)
IGE1				1.0584 (0.2947)*** (0.3557)***	1.9193 (0.3111)*** (0.6291)***	2.5936 (0.3726)*** (0.8933)***	1.0074 (0.2818)*** (0.3285)***	1.9102 (0.3060)*** (0.6096)***	2.5589 (0.3758)*** (0.8631)***	0.9166 (0.2950)*** (0.3116)***	1.8040 (0.3575)*** (0.5712)***	2.6584 (0.4728)*** (0.6860)***
AGE							0.0444 (0.0175)** (0.0182)**	0.0175 (0.0146) (0.0172)	0.0157 (0.0161) (0.0192)	0.0423 (0.0174)** (0.0178)**	0.0155 (0.0155) (0.0172)	0.0133 (0.0157) (0.0178)
LFSTOCK										-0.5085 (0.5873) (0.4853)	0.1098 (0.8206) (0.9988)	0.9495 (1.2682) (1.7498)
ECACRA												
UNEM												
INACTIVE												
ECACRF												
OBS.	392			392			392			392		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
EMN	-1.3252 (0.1041)*** (0.1415)***	-1.3678 (0.1478)*** (0.1963)***	-1.3097 (0.1379)*** (0.1655)***	-1.3239 (0.1104)*** (0.1439)***	-1.3340 (0.1268)*** (0.1594)***	-1.3343 (0.1285)*** (0.1428)***	-1.3016 (0.1106)*** (0.1411)***	-1.2905 (0.1299)*** (0.1625)***	-1.3062 (0.1456)*** (0.1664)***			
IMN	0.0016 (0.0139) (0.0084)	0.0248 (0.0190) (0.0173)	0.0080 (0.0171) (0.0145)	-0.0024 (0.0146) (0.0087)	0.0080 (0.0171) (0.0131)	-0.0025 (0.0166) (0.0121)	-0.0014 (0.0149) (0.0092)	0.0109 (0.0182) (0.0151)	-0.0002 (0.0186) (0.0146)			
IGE1	0.7199 (0.2755)*** (0.2862)**	0.4135 (0.4323) (0.5027)	0.9974 (0.5290)* (0.5877)*	0.8870 (0.2879)*** (0.3653)**	0.8276 (0.3777)** (0.4036)**	1.3005 (0.4709)*** (0.4774)***	0.8500 (0.2905)*** (0.3554)**	0.6281 (0.3709)* (0.3541)*	1.0146 (0.5171)* (0.5664)*			
AGE	0.0242 (0.0159) (0.0173)	0.0317 (0.0193) (0.0233)	0.0138 (0.0176) (0.0191)	0.0295 (0.0168)* (0.0187)	0.0383 (0.0170)** (0.0252)	0.0184 (0.0170) (0.0229)	0.0286 (0.0174) (0.0196)	0.0506 (0.0191)*** (0.0264)*	0.0442 (0.0196)** (0.0236)*			
LFSTOCK												
ECACRA	-0.0244 (0.0079)*** (0.0110)**	-0.0392 (0.0136)*** (0.0225)*	-0.0436 (0.0146)*** (0.0234)*									
UNEM				-0.5645 (0.9049) (0.7823)	-1.3964 (1.2954) (1.8041)	0.5442 (1.5256) (1.6406)						
INACTIVE							0.2723 (0.6836) (0.6438)	-2.0501 (1.1022)* (1.1537)*	-4.7262 (1.7725)*** (1.6964)***			
ECACRF				-0.0164 (0.0075)** (0.0108)	-0.0243 (0.0106)** (0.0183)	-0.0311 (0.0121)*** (0.0206)	-0.0160 (0.0077)** (0.0112)	-0.0278 (0.0113)** (0.0188)	-0.0597 (0.0186)*** (0.0240)**			
OBS.	325			325			325					

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator.

6.4.1.2 Independent Income Variable: Income of Normally Working People

(a) Static Model

The FEs model is the most appropriate model to determine the impact of income distribution on inequality of the education level completed ($EGE1$). The FEs results of the study are displayed in Table 6.14, while the OLS and REs results are presented in Appendices A6.8 and A6.16, respectively.

In Regression 1, the unconditional impact of educational attainment (EMN) on educational inequality has been analysed. The addition of income distribution for normally working people (Regression 2) and of control variables (Regressions 3–9) does not change the estimated effect of the variable for the average education level completed. The conditional impact is negative and statistically significant at the one per cent level. Additionally, the educational attainment coefficient fairly constant throughout the different specifications. Once more, the results show that the expansion of educational opportunity enables people to take up higher formal education levels, because the increased opportunity of acquiring higher education helps individuals to improve their socioeconomic circumstances and to achieve appropriate positions in the regional economy, regardless of their social background.

Regression 2 allows us to assess whether the distribution of income among normally working people is capable of explaining the variation in educational inequality. First, Regression 2 concedes the unclear effect of the income per capita of normally working people (NMN) on inequality in the education level completed. The inclusion of the other elements of the model (Regressions 3–9) does not change this result. While educational attainment reduces educational inequality, income per capita seems not to affect educational inequality. Hence the expansion of state education promotes a meritocratic basis for educational attainment, regardless not only of the social background, but also of the economic background of the individual. Second, the impact of income inequality among normally working people ($NGE1$) on educational inequality is positive and statistically significant. When the additional covariates of the model are added, the positive relationship still persists, indicating the robustness of the results. The analysis carried out highlights the fact that the rich and normally working people have greater educational opportunities than the poor. The results obtained reveal the role of human capital returns at different education levels. Greater equality of educational opportunities may only be achieved through equality at all levels and stages of education. Consequently, Regression 2 shows that the citizens of European regions become better off through education at a different rate.

Regressions 1 and 2 offered a simple framework for understanding the differences in levels of educational inequality across EU regions and over time. The next step is to test whether a set of additional structural variables provides insight into educational inequality. The sign and significance of the coefficients on the additional time-variant variables is the same no matter how income inequality is measured (either for the whole of the population or for normally working people). Regression 3, for instance, controls for population ageing (AGE). As in the regressions for income distribution for the population as a whole, the impact of the average age of respondents on human capital inequality seems to be unclear, because it is statistically significant in Regression 8 only, which shows that an increasing number of elderly and probably retired people lead to a rise in educational inequality. The impact of the percentage of normally working people $(LFSTOCK)$, of unemployed respondents $(UNEM)$ and of inactive respondents $(INACTIVE)$ is unclear, while the economic activity rate of total population $(ECACRA)$ and of women $(ECACRF)$ is negatively associated with educational inequality. Regressions 8 and 9 show that while the effect of urbanisation decreased gradually between 1998 and 2000, the effect of latitude was higher in 1999. The respective OLS and FEs results (Appendices A6.8 and A6.16) display the positive coefficient on urbanisation and the negative coefficient on latitude.

The identifying time-variant determinants explain up to 75.81 per cent of the variation in educational inequality levels across regions and over time. In terms of goodness-of-fit, it is likely to indicate good FEs models.

Appendices A6.8 and A6.16 show that human capital inequality is higher in liberal welfare states and in Anglican areas such as the United Kingdom. Once more, taking into account the standardised coefficients (Appendix A6.2), educational attainment explains a major part of the variation in educational inequality.

Table 6.14: FEs: Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EMN	-1.0761 (0.0251)*** _(0.0225)_***	-1.0932 (0.0315)*** _(0.0338)_***	-1.0933 (0.0315)*** _(0.0338)_***	-1.0848 (0.0326)*** _(0.0340)_***	-1.1281 (0.0356)*** _(0.0399)_***	-1.1260 (0.0362)*** _(0.0407)_***	-1.1273 (0.0367)*** _(0.0398)_***	-0.8903 (0.0623)*** _(0.0476)_***	-1.1808 (0.0428)*** _(0.0536)_***
NMN		0.0019 (0.0021) _(0.0016)_	0.0016 (0.0021) _(0.0016)_	0.0019 (0.0021) _(0.0016)_	0.0014 (0.0027) _(0.0019)_	0.0019 (0.0027) _(0.0019)_	0.0018 (0.0027) _(0.0019)_	0.0022 (0.0039) _(0.0046)_	-0.0009 (0.0032) _(0.0026)_
NGE1		0.2020 (0.0864)** _(0.0665)_***	0.2024 (0.0865)** _(0.0667)_***	0.1925 (0.0870)** _(0.0671)_***	0.1371 (0.1093) _(0.0824)_*	0.1559 (0.1105) _(0.0788)_**	0.1623 (0.1096) _(0.0807)_**	0.2366 (0.1329)* _(0.1088)_**	0.1737 (0.1103) _(0.0847)_**
AGE			0.0022 (0.0043) _(0.0039)_	0.0021 (0.0043) _(0.0038)_	0.0036 (0.0047) _(0.0046)_	0.0052 (0.0049) _(0.0047)_	0.0045 (0.0048) _(0.0050)_	0.0102 (0.0058)* _(0.0052)_**	-0.0002 (0.0051) _(0.0048)_
LFSTOCK				-0.1665 (0.1658) _(0.1375)_					
ECACRA					-0.0102 (0.0031)*** _(0.0034)_***				
UNEM						0.1463 (0.3193) _(0.2590)_		0.3492 (0.4478) _(0.4573)_	0.3877 (0.3233) _(0.2768)_
INACTIVE							0.0254 (0.2073) _(0.2084)_		
ECACRF						-0.0059 (0.0027)** _(0.0029)_**	-0.0061 (0.0026)** _(0.0027)_**	-0.0098 (0.0036)*** _(0.0038)_**	-0.0090 (0.0028)*** _(0.0030)_***
YR96*URBANDPAV								-0.0147 (0.0316) _(0.0434)_	
YR97*URBANDPAV								-0.0158 (0.0323) _(0.0391)_	
YR98*URBANDPAV								-0.0879 (0.0349)** _(0.0381)_**	
YR99*URBANDPAV								-0.0860 (0.0369)** _(0.0419)_**	
YR00*URBANDPAV								-0.1049 (0.0390)*** _(0.0484)_**	
YR96*LAT									-0.0002 (0.0003) _(0.0003)_
YR97*LAT									0.0000 (0.0003) _(0.0002)_
YR98*LAT									0.0003 (0.0003) _(0.0002)_
YR99*LAT									0.0009 (0.0003)*** _(0.0003)_***
YR00*LAT									0.0006 (0.0003)* _(0.0003)_*
CONSTANT	1.5964 (0.0189)*** _(0.0176)_***	1.5355 (0.0307)*** _(0.0197)_***	1.4406 (0.1887)*** _(0.1694)_***	1.5250 (0.2066)*** _(0.1990)_***	1.9704 (0.2765)*** _(0.2747)_***	1.5812 (0.2566)*** _(0.2534)_***	1.6215 (0.2416)*** _(0.2103)_***	1.4137 (0.3351)*** _(0.3134)_***	2.0225 (0.2848)*** _(0.2789)_***
ADJ R-SQ	0.7888	0.7916	0.7918	0.7922	0.7609	0.7581	0.7580	0.8347	0.7684
OBS.	596	596	596	596	513	513	513	299	513
LM TEST (p-value)	1134.37 (0.0000)	1064.72 (0.0000)	1068.11 (0.0000)	906.42 (0.0000)	793.34 (0.0000)	809.09 (0.0000)	788.76 (0.0000)	466.20 (0.0000)	822.97 (0.0000)
HAUSMAN TEST (p-value)	23.91 (0.0000)	47.16 (0.0000)	43.05 (0.0000)	128.82 (0.0000)	50.79 (0.0000)	61.08 (0.0000)	67.81 (0.0000)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*)_, _(**)_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

(b) Dynamic Model

Table 6.15 presents the long-run coefficients on the educational inequality (*EGE*1) variables. The validity of the model is conformed by the tests[88] reported in Appendix A6.24, where the short-run coefficients are also displayed.

First, all the equations reject that the lagged human capital inequality is zero. The pure long-run impact of educational attainment (*EMN*) on educational inequality (Regression 1) has already been presented. Nevertheless, the conditional impact of human capital stock remains negative and statistically significant at the one per cent level. Introducing, income distribution for normally working people into the equations, the effect of income per capita (*NMN*) is negative but sensitive to the model specifications, while income inequality (*NGE*1) is positively associated with human capital inequality. The same long-run results are produced when the income distribution for the population as a whole is considered as the explanatory variable. Hence, the results are robust to changes in the measure of 'income per capita' and 'income inequality' and under many different dynamic model specifications.

The coefficient on population ageing (*AGE*) is positive and robust to the model specifications, because it is statistically significant in 11 out of 15 equations, especially when the explanatory variables are assumed to be strictly exogenous or predetermined. As in the regressions with income distribution for the population as a whole, the impact of the percentage of normally working respondents (*LFSTOCK*) is not clear, while that of economic activity rate of total population (*ECACRA*) is negative and statistically significant, no matter what the explanatory variables are assumed to be. The impact of unemployment (*UNEM*) on educational inequality is not clear. Although the OLS, FEs and REs coefficients on inactivity (*INACTIVE*) are not statistically significant, the long-run GMM results (Regression 7) show that the predetermined and endogenous impact of the percentage of inactive respondents on educational inequality is negative and statistically

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88 The Sargan tests reject the overidentifying restrictions in all equations. The tests for serial correlation reject the absence of first-order, except for equations 2c, 3c and 4c (both homoskedastic and heteroskedastic case); while they reject the absence of second-order in the heteroskedastic equations 2b, 2c and 4c. Based on the specification tests, the heteroskedastic equation 2b is the most appropriate.

significant. Finally, Regressions 6 and 7 show the negative impact of the variable for women's access to work (*ECACRF*) on educational inequality.

It is worth noting that apart from the coefficient on income per capita for normally working people, which is not statistically significant in the static models, but negative and non-robust in the dynamic ones, all the other regressors have been found to be robust, in the sense that their estimated parameters keep the same sign and are statistically significant in the same static and dynamic model specifications. The coefficients on educational attainment and income inequality are not sensitive to the inclusion of different control variables.

Table 6.15: Long Run GMM: Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

	REGRESSION (1)			REGRESSION (2)			REGRESSION (3)			REGRESSION (4)		
	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
EMN	-1.1667 (0.0982)*** (0.1254)***	-1.3155 (0.1363)*** (0.2353)***	-1.7170 (0.2330)*** (0.4263)***	-1.3019 (0.1289)*** (0.1883)***	-1.2910 (0.1329)*** (0.2016)***	-1.4928 (0.1662)*** (0.2426)***	-1.2233 (0.1239)*** (0.1703)***	-1.2465 (0.1306)*** (0.1827)***	-1.4775 (0.1658)*** (0.2272)***	-1.2099 (0.1282)*** (0.1755)***	-1.2587 (0.1289)*** (0.1714)***	-1.3997 (0.1583)*** (0.1847)***
NMN				0.0062 (0.0098) (0.0100)	-0.0146 (0.0107) (0.0106)	-0.0299 (0.0164)* (0.0203)	0.0018 (0.0095) (0.0088)	-0.0159 (0.0105) (0.0101)	-0.0318 (0.0166)* (0.0202)	0.0014 (0.0097) (0.0074)	-0.0204 (0.0105)* (0.0102)**	-0.0285 (0.0167)* (0.0189)
NGE1				0.7330 (0.3164)** (0.3056)**	1.6640 (0.3670)*** (0.5793)***	3.0082 (0.5358)*** (1.2096)**	0.6635 (0.3009)** (0.2799)**	1.5710 (0.3612)*** (0.5348)***	2.9019 (0.5357)*** (1.1381)**	0.6502 (0.3048)** (0.2716)**	1.5962 (0.3567)*** (0.5078)***	2.3961 (0.5495)*** (0.8270)***
AGE							0.0597 (0.0203)*** (0.0205)***	0.0342 (0.0162)** (0.0177)*	0.0267 (0.0168) (0.0196)	0.0568 (0.0201)*** (0.0199)***	0.0326 (0.0158)** (0.0174)*	0.0235 (0.0159) (0.0193)
LFSTOCK										0.0707 (0.6541) (0.6347)	-0.4246 (0.8040) (1.0760)	-1.8224 (1.2169) (2.0221)
ECACRA												
UNEM												
INACTIVE												
ECACRF												
OBS.	392			392			392			392		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
EMN	-1.2890 (0.1058)*** (0.1467)***	-1.2203 (0.1332)*** (0.1697)***	-1.3154 (0.1594)*** (0.2051)***	-1.2960 (0.1149)*** (0.1535)***	-1.1766 (0.1245)*** (0.1424)***	-1.2666 (0.1423)*** (0.1723)***	-1.2996 (0.1191)*** (0.1590)***	-1.2536 (0.1315)*** (0.1735)***	-1.3246 (0.1573)*** (0.1997)***			
NMN	-0.0016 (0.0102) (0.0072)	0.0074 (0.0125) (0.0094)	0.0071 (0.0145) (0.0124)	-0.0039 (0.0111) (0.0083)	-0.0004 (0.0122) (0.0090)	0.0002 (0.0132) (0.0101)	-0.0026 (0.0112) (0.0077)	0.0004 (0.0123) (0.0088)	0.0012 (0.0134) (0.0099)			
NGE1	0.4273 (0.3026) (0.2369)*	0.5495 (0.4422) (0.5018)	1.3247 (0.7693)* (0.8087)	0.6372 (0.3269)* (0.3203)**	0.8876 (0.4090)** (0.3694)**	1.6243 (0.6992)** (0.6970)**	0.5733 (0.3283)* (0.2945)*	0.7539 (0.4057)* (0.3121)**	1.0988 (0.7294) (0.7919)			
AGE	0.0327 (0.0177)* (0.0177)*	0.0406 (0.0184)** (0.0225)*	0.0095 (0.0218) (0.0257)	0.0376 (0.0190)** (0.0198)*	0.0506 (0.0179)*** (0.0251)**	0.0241 (0.0201) (0.0250)	0.0378 (0.0197)* (0.0208)*	0.0548 (0.0191)*** (0.0258)**	0.0419 (0.0221)* (0.0242)*			
LFSTOCK												
ECACRA	-0.0284 (0.0084)*** (0.0122)**	-0.0369 (0.0118)*** (0.0215)*	-0.0436 (0.0150)*** (0.0263)*									
UNEM				-1.0489 (1.0521) (1.1002)	-1.6125 (1.2455) (1.5632)	-0.5911 (1.7971) (1.9354)						
INACTIVE							-0.2514 (0.7566) (0.6985)	-2.6880 (1.1056)** (1.3632)**	-4.2736 (1.9399)** (2.0418)**			
ECACRF				-0.0204 (0.0084)** (0.0122)*	-0.0267 (0.0104)** (0.0167)	-0.0328 (0.0133)** (0.0229)	-0.0198 (0.0087)** (0.0127)	-0.0300 (0.0109)*** (0.0172)*	-0.0617 (0.0199)*** (0.0238)**			
OBS.	325			325			325					

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. (*), (**) and (***) denote the significance of the White (1980) estimator.

6.4.2 Inequality in the Age at which the Highest Education Level was Completed

6.4.2.1 Independent Income Variable: Income of the Population as a Whole

(a) Static Model

The OLS, FEs and REs models of inequality in the age at which the highest education level was completed ($AGE1$) are estimated. The specification tests are in favour of the FEs models. Table 6.16 displays the FEs results, while the OLS and the REs are presented in Appendices A6.9 and A6.17, respectively.

Table 6.16: FEs: Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AMN	0.0042 (0.0005)*** *(0.0008)******	0.0042 (0.0005)*** *(0.0007)******	0.0042 (0.0005)*** *(0.0007)******	0.0042 (0.0005)*** *(0.0007)******	0.0038 (0.0006)*** *(0.0007)******	0.0039 (0.0006)*** *(0.0008)******	0.0037 (0.0006)*** *(0.0008)******	0.0093 (0.0015)*** *(0.0016)******	0.0045 (0.0007)*** *(0.0009)******
IMN		0.0002 (0.0001) *(0.0002)*	0.0001 (0.0001) *(0.0002)*	0.0001 (0.0002) *(0.0002)*	0.0002 (0.0002) *(0.0003)*	0.0002 (0.0002) *(0.0003)*	0.0001 (0.0002) *(0.0003)*	0.0005 (0.0004) *(0.0003)**	0.0007 (0.0003)** *(0.0003)***
IGE1		0.0234 (0.0059)*** *(0.0055)******	0.0241 (0.0060)*** *(0.0056)******	0.0242 (0.0061)*** *(0.0054)******	0.0312 (0.0077)*** *(0.0078)******	0.0281 (0.0078)*** *(0.0078)******	0.0312 (0.0076)*** *(0.0077)******	0.0149 (0.0110) *(0.0103)*	0.0219 (0.0083)*** *(0.0081)******
AGE			0.0004 (0.0003) *(0.0004)*	0.0004 (0.0003) *(0.0004)*	0.0004 (0.0003) *(0.0004)*	0.0005 (0.0003) *(0.0004)*	0.0005 (0.0003) *(0.0003)*	0.0006 (0.0005) *(0.0004)*	0.0007 (0.0004)* *(0.0004)**
LFSTOCK				0.0007 (0.0113) *(0.0112)*					
ECACRA					0.0002 (0.0002) *(0.0002)*				
UNEM						0.0390 (0.0226)* *(0.0192)****		0.0268 (0.0351) *(0.0344)*	0.0361 (0.0230) *(0.0190)**
INACTIVE							-0.0260 (0.0144)* *(0.0154)**		
ECACRF						0.0002 (0.0002) *(0.0002)*	0.0001 (0.0002) *(0.0002)*	0.0001 (0.0003) *(0.0002)*	0.0002 (0.0002) *(0.0002)*
YR96*URBANDPAV								-0.0004 (0.0025) *(0.0017)*	
YR97*URBANDPAV								-0.0023 (0.0024) *(0.0017)*	
YR98*URBANDPAV								-0.0021 (0.0025) *(0.0018)*	
YR99*URBANDPAV								-0.0021 (0.0028) *(0.0020)*	
YR00*URBANDPAV								-0.0029 (0.0032) *(0.0024)*	
YR96*LAT									0.0000 (0.0000) *(0.0000)*
YR97*LAT									0.0000 (0.0000) *(0.0000)*
YR98*LAT									0.0000 (0.0000) *(0.0000)*
YR99*LAT									0.0000 (0.0000) *(0.0000)*
YR00*LAT									-0.0001 (0.0000)* *(0.0000)****
CONSTANT	-0.0341 (0.0095)*** *(0.0141)****	-0.0453 (0.0098)*** *(0.0127)******	-0.0610 (0.0163)*** *(0.0164)******	-0.0614 (0.0172)*** *(0.0168)******	-0.0710 (0.0233)*** *(0.0190)******	-0.0762 (0.0212)*** *(0.0195)******	-0.0567 (0.0206)*** *(0.0193)******	-0.1620 (0.0367)*** *(0.0350)******	-0.0990 (0.0255)*** *(0.0251)******
ADJ R-SQ	0.1314	0.1646	0.1673	0.1673	0.1591	0.1654	0.1662	0.1128	0.1797
OBS.	534	534	534	534	455	455	455	299	455
LM TEST (p-value)	1172.18 (0.0000)	680.95 (0.0000)	693.42 (0.0000)	666.96 (0.0000)	630.85 (0.0000)	605.00 (0.0000)	600.39 (0.0000)	403.60 (0.0000)	621.52 (0.0000)
HAUSMAN TEST (p-value)	5.01 (0.0252)	113.42 (0.0000)	83.17 (0.0000)	*52.00* *(0.0000)*	47.64 (0.0000)	46.72 (0.0000)	33.17 (0.0000)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. LM TEST is the Lagrange Multiplier test for the random effects model based on the OLS residuals (Breusch and Paga,n 1980). HAUSMAN TEST is the Hausman (1978) test for fixed or random effects.

First, it would be interesting to know the pure effects of educational attainment (AMN), which is measured in terms of the average age at which the highest education level was completed, on educational inequality (Regression 1). The coefficient on educational achievement is positive and statistically significant at the one per cent level. This determinant explains approximately 13.14 per cent of the variation in inequality. The sign of the coefficient reported is small in magnitude. Regressions 2–9 also show the positive coefficient on educational attainment which remains statistically significant at the one per cent level, both in the homoskedastic and heteroskedastic case. I interpret the positive coefficient as evidence that an increase in educational attainment is more likely to be the consequence of an increase in private educational expenditures rather than the consequence of an increase in state educational grants or of a decrease in tuition fees. State grants are not enough so as to provide educational opportunities for all young people to continue their studies to higher education levels. To put it another way, rich people are more likely to continue their studies at an older age than the poor. While the first proxy for human capital stock (average education level completed) has a negative effect on the respective human capital inequality, the second proxy (average age at which the highest level of education was completed) has a positive effect. One possible explanation for this difference may be the broader concept of human capital that is embodied in the latter proxy. This proxy is likely to encompass experience, improved general and specific information about labour market institutions, learning-by-doing and on-the-job training, from the positive point of view, and economic inactivity and short-term unemployment, from the negative point of view.

Second, the introduction of the income distribution for the population as a whole measured by income per capita (IMN) and income inequality ($IGE1$) is analysed. Regressions 2–9 idicate that the higher the income per capita and the income inequality, the higher the human capital inequality. However, while the coefficient on income inequality is robust to the model specification, the coefficient on income per capita is very fragile since it is statistically significant only in Regressions 8 and 9. The sign of the income per capita coefficient in Regressions 2–7 is positive, but statistically insignificant. The basic argument is that rich people have greater educational opportunities than the poor. Rich people have better job chances and greater opportunities to take up an otherwise profitable education level, if it is necessary. Additionally, rich people are more likely to take time out of the labour market so as to continue their studies, even when they are older. Due to the causality effects, a positive impact of income inequality on inequality in the age at which the highest education level was completed is likely to reflect the responsiveness of the EU labour market to differences in qualifications and skills.

Third, the impact of the control time-variant variables on educational inequality is analysed in Regressions 3–9. The coefficients on population ageing (*AGE*) (except for Regression 9) and access to work (both access to work of the total population — measured by the percentage of normally working respondents (*LFSTOCK*) and by the economic activity rate (*ECACRA*) — and women's access to work (*ECACRF*)) are not statistically significant, which suggests that their impact on human capital inequality is not clear. I then control for unemployment (*UNEM*) and inactivity (*INACTIVE*) to lessen the possibility that this proxy for human capital encompasses short-term unemployment and economic inactivity, respectively. Regressions 6 and 9 show that unemployment is positively associated with inequality. Students from more affluent families have access to more accurate labour market information than students from unemployed and poor families. On the other hand, Regression 7 shows the negative relationship between inactivity and inequality. This is perhaps because more young people remain outside the labour market in order to continue their studies (Rodríguez-Pose, 1998). Combining the effect of unemployment and inactivity, Regressions 6 and 7 show that high unemployment may discourage young people from participating in the labour market, which implies a large increase in human capital in the short-term, while a high level of economic inactivity among young people is likely to push them to continue their studies in order to gain more skills and knowledge in the long-term.

Regressions 8 and 9 check whether the effects of urbanisation (*URBANDPAV*) and latitude (*LAT*), respectively, on educational inequality have changed over the period 1995–2000. The effects of urbanisation are almost the same between 1995 and 2000, while the effects of latitude are lower in 2000. The OLS and REs results of these regressions (Appendices A6.9 and A6.17) test for the EU urban-rural and EU north-south patterns. The coefficients on both urbanisation and latitude are negative. They show that human capital inequality is higher in the southern areas of Europe and in the rural regions.

Appendices A6.9 and A6.17 show the OLS and REs results for the welfare state (Regression 10), religion (Regression 11) and family structure (Regression 12) variables. Human capital inequality is lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures. Finally, taking into account the standardised coefficients (Appendix A6.2), educational attainment accounts for a major part of the variation in inequality in the age at which the highest education level was completed, as it does for inequality in the education level completed.

(b) Dynamic Model

Table 6.17 displays the long-run GMM regression results on human capital inequality as measured by the age at which the highest education level was completed. The validity of the results is confirmed by the test results[89] reported in Appendix A6.25, which also displays the short-run coefficients.

Regression 1 of Appendix A6.25 shows that the coefficient on the lagged dependent variable is positive and statistically significant. I expected to find that educational inequality in the current period depends on educational inequality in the lagged one-year period. Nevertheless, when the income per capita and the income inequality covariates of the model are added, somewhat surprisingly, the coefficient on the lagged dependent variable is insignificant. This finding was subjected to the sensitivity analysis. Considering the long-run coefficients (Table 6.17), first of all, the impact of the average age at which the highest education level was completed (*AMN*) on age inequality is not clear, because the coefficients on educational attainment are not statistically significant. On introducing income distribution for the population as a whole, both income per capita and income inequality are positively associated with educational inequality, but they are sensitive to the assumption of the explanatory variables. While the coefficients on income per capita (*IMN*) are statistically significant only when the independent variables are strictly exogenous, the coefficients on income inequality (*IGE*1) are statistically significant when

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[89] The Sargan tests accept the overidentifying restrictions in Regressions 4, 5 and 7, only when the explanatory variables are assumed to be predetermined or endogenous. The tests for serial correlation reject the absence of first-order except for equations2b, 2c, 3b, 3c, 4c (robust and non-robust standard errors), 4b and 7b (robust standard errors). On the other hand, the tests accept the absence of second-order except for equations 2c, 3b, 3c (both robust and non-robust standard errors) and 2b (non-robust standard errors). Hence, there is no any equation which satisfies all the specification tests.

the independent variables are predetermined or endogenous. The latter are also significant in equation 6c (homoskedastic case). It is of note that the coefficients on the control variables (population ageing (AGE), economic activity rate of the total population $(ECACRA)$ and of women $(ECACRF)$, the percentage of unemployed respondents $(UNEM)$ and the percentage of inactive respondents $(INACTIVE)$) are insignificant, except for the percentage of normally working respondents $(LFSTOCK)$ which is statistically significant at the ten per cent level in equation 4c (homoskedastic case).

Table 6.17: Long Run GMM: Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

	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
AMN	-0.0036 (0.0051) (0.0068)	-0.0002 (0.0034) (0.0042)	-0.0003 (0.0048) (0.0054)	0.0012 (0.0020) (0.0029)	0.0006 (0.0015) (0.0013)	0.0001 (0.0016) (0.0015)	0.0014 (0.0018) (0.0026)	0.0012 (0.0014) (0.0012)	0.0004 (0.0016) (0.0015)	0.0015 (0.0018) (0.0026)	0.0015 (0.0015) (0.0014)	0.0000 (0.0017) (0.0018)
IMN				0.0013 (0.0005)** (0.0005)**	0.0002 (0.0005) (0.0006)	0.0001 (0.0006) (0.0008)	0.0012 (0.0005)** (0.0005)**	0.0002 (0.0005) (0.0006)	0.0001 (0.0006) (0.0009)	0.0014 (0.0006)** (0.0007)**	0.0003 (0.0005) (0.0006)	0.0002 (0.0006) (0.0009)
IGE1				0.0163 (0.0161) (0.0157)	0.0746 (0.0159)*** (0.0254)***	0.0822 (0.0214)*** (0.0291)***	0.0172 (0.0154) (0.0147)	0.0713 (0.0155)*** (0.0245)***	0.0809 (0.0212)*** (0.0297)***	0.0132 (0.0165) (0.0135)	0.0578 (0.0177)*** (0.0223)**	0.0749 (0.0215)*** (0.0289)**
AGE							0.0009 (0.0008) (0.0009)	0.0008 (0.0006) (0.0007)	0.0005 (0.0006) (0.0006)	0.0008 (0.0009) (0.0009)	0.0007 (0.0007) (0.0007)	0.0002 (0.0006) (0.0007)
LFSTOCK										-0.0357 (0.0328) (0.0363)	-0.0338 (0.0360) (0.0390)	-0.0878 (0.0513)* (0.0570)
ECACRA												
UNEM												
INACTIVE												
ECACRF												
OBS.	348			348			348			348		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
AMN	0.0013 (0.0016) (0.0023)	0.0005 (0.0020) (0.0019)	0.0011 (0.0020) (0.0019)	0.0012 (0.0016) (0.0024)	0.0009 (0.0022) (0.0020)	0.0013 (0.0023) (0.0024)	0.0013 (0.0017) (0.0023)	0.0015 (0.0020) (0.0018)	0.0008 (0.0021) (0.0021)			
IMN	0.0012 (0.0006)* (0.0006)**	-0.0001 (0.0008) (0.0007)	0.0002 (0.0008) (0.0008)	0.0013 (0.0006)** (0.0007)*	0.0001 (0.0008) (0.0008)	0.0002 (0.0009) (0.0009)	0.0013 (0.0007)* (0.0007)*	0.0004 (0.0009) (0.0007)	0.0002 (0.0010) (0.0008)			
IGE1	0.0259 (0.0163) (0.0165)	0.0809 (0.0235)*** (0.0305)***	0.0825 (0.0273)*** (0.0358)**	0.0277 (0.0156)* (0.0174)	0.0724 (0.0208)*** (0.0259)***	0.0671 (0.0246)*** (0.0289)**	0.0259 (0.0164) (0.0159)	0.0457 (0.0242)* (0.0235)*	0.0622 (0.0261)** (0.0306)**			
AGE	0.0010 (0.0009) (0.0009)	0.0012 (0.0010) (0.0009)	0.0006 (0.0009) (0.0008)	0.0010 (0.0008) (0.0008)	0.0010 (0.0010) (0.0009)	0.0006 (0.0009) (0.0008)	0.0008 (0.0009) (0.0008)	0.0003 (0.0012) (0.0010)	-0.0001 (0.0011) (0.0010)			
LFSTOCK												
ECACRA	0.0002 (0.0005) (0.0004)	-0.0002 (0.0010) (0.0011)	0.0002 (0.0011) (0.0015)									
UNEM				-0.0317 (0.0476) (0.0439)	0.0041 (0.0721) (0.0666)	0.0662 (0.0897) (0.0942)						
INACTIVE							0.0285 (0.0385) (0.0415)	0.1131 (0.0790) (0.0728)	0.0796 (0.0970) (0.1054)			
ECACRF				0.0005 (0.0004) (0.0005)	0.0002 (0.0008) (0.0007)	0.0001 (0.0008) (0.0009)	0.0006 (0.0004) (0.0005)	0.0000 (0.0008) (0.0006)	-0.0001 (0.0011) (0.0013)			
OBS.	285			285			285					

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator.

6.4.2.2 Independent Income Variable: Income of Normally Working People

(a) Static Model

The FEs model is the most appropriate model to explore the impact of income distribution among normally working people on human capital inequality as measured by the age at which the highest education level was completed ($AGE1$). The FEs results and the specification tests are displayed in Table 6.18, while the OLS and REs results are presented in Appendices A6.10 and A6.18, respectively.

The positive and statistically significant unconditional impact of educational attainment (AMN) on educational inequality has already been analysed (Table 6.16). The conditional influence is also positive and statistically significant at the one per cent level. Hence, the coefficients on educational achievement when the income of normally working people is considered as the explanatory variable are approximately the same as the coefficients when income of the population as a whole is considered as the explanatory income variable. The income per capita regressor (NMN) has been found to be very fragile (Regressions 2–8). In Regression 9, the coefficient on income per capita is positive and significant (as in income distribution for the population as a whole). The income inequality regressor ($NGE1$), on the other hand, is positive and robust to the inclusion of different control variables.

Taking into account the impact of control variables on inequality in the age at which the highest education level was completed, the sign and significance of coefficients are the same as in the regressions with the income distribution for the population as a whole explanatory variables. More specifically, the impact of population ageing (AGE) is positive and significant in Regression 9 only. The coefficients on access to work (both of the total population — measured by the percentage of normally working respondents ($LFSTOCK$) and by the economic activity rate ($ECACRA$) — and of women ($ECACRF$)) are insignificant. Regressions 6 and 9 show that unemployment is positively associated with educational inequality, while Regression 7 displays the negative relationship between inactivity and inequality. Regressions 8 and 9 show that the effects of urbanisation ($URBANDPAV$) are almost the same between 1995 and 2000, while the effects of latitude (LAT) are lower in 2000. The OLS and REs results of these regressions (Appendices

A6.10 and A6.18) display once again that human capital inequality is higher in the southern areas of Europe and in the rural regions.

The OLS and REs results (Appendices A6.10 and A6.18) for the welfare state (Regression 10), religion (Regression 11) and family structure (Regression 12) variables demonstrate that educational inequality is lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures. Finally, taking into account the standardised coefficients (Appendix A6.2), educational attainment accounts for a major part of the variation in inequality in the age at which the highest education level was completed.

Table 6.18: FEs: Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AMN	0.0042 (0.0005)*** (0.0008)***	0.0041 (0.0005)*** (0.0008)***	0.0040 (0.0005)*** (0.0008)***	0.0041 (0.0005)*** (0.0008)***	0.0037 (0.0006)*** (0.0008)***	0.0039 (0.0006)*** (0.0008)***	0.0036 (0.0006)*** (0.0008)***	0.0095 (0.0015)*** (0.0016)***	0.0046 (0.0007)*** (0.0009)***
NMN		0.0001 (0.0001) (0.0002)	0.0001 (0.0001) (0.0001)	0.0001 (0.0001) (0.0001)	0.0002 (0.0002) (0.0002)	0.0002 (0.0002) (0.0002)	0.0002 (0.0002) (0.0002)	0.0002 (0.0003) (0.0002)	0.0006 (0.0002)*** (0.0002)**
NGE1		0.0147 (0.0059)** (0.0049)***	0.0147 (0.0059)** (0.0049)***	0.0145 (0.0060)** (0.0049)***	0.0179 (0.0079)** (0.0066)***	0.0153 (0.0079)* (0.0064)**	0.0182 (0.0078)** (0.0063)***	0.0152 (0.0104) (0.0084)*	0.0105 (0.0080) (0.0062)*
AGE			0.0002 (0.0003) (0.0004)	0.0002 (0.0003) (0.0004)	0.0002 (0.0003) (0.0004)	0.0004 (0.0003) (0.0004)	0.0003 (0.0003) (0.0003)	0.0005 (0.0005) (0.0004)	0.0006 (0.0004)* (0.0004)
LFSTOCK				-0.0028 (0.0112) (0.0122)					
ECACRA					0.0000 (0.0002) (0.0002)				
UNEM						0.0484 (0.0226)** (0.0189)**		0.0266 (0.0350) (0.0333)	0.0403 (0.0230)* (0.0182)**
INACTIVE							-0.0259 (0.0145)* (0.0167)		
ECACRF						0.0000 (0.0002) (0.0002)	-0.0001 (0.0002) (0.0002)	0.0001 (0.0003) (0.0002)	0.0002 (0.0002) (0.0002)
YR96*URBANDPAV								-0.0012 (0.0024) (0.0017)	0.0000 (0.0000) (0.0000)
YR97*URBANDPAV								-0.0023 (0.0024) (0.0017)	0.0000 (0.0000) (0.0000)
YR98*URBANDPAV								-0.0023 (0.0025) (0.0019)	0.0000 (0.0000) (0.0000)
YR99*URBANDPAV								-0.0020 (0.0027) (0.0021)	0.0000 (0.0000) (0.0000)
YR00*URBANDPAV								-0.0022 (0.0030) (0.0021)	-0.0001 (0.0000)** (0.0000)**
YR96*LAT									
YR97*LAT									
YR98*LAT									
YR99*LAT									
YR00*LAT									
CONSTANT	-0.0341 (0.0095)*** (0.0141)**	-0.0369 (0.0095)*** (0.0137)***	-0.0465 (0.0158)*** (0.0171)***	-0.0455 (0.0163)*** (0.0180)**	-0.0391 (0.0211)* (0.0181)**	-0.0560 (0.0201)*** (0.0198)***	-0.0294 (0.0191) (0.0180)	-0.1559 (0.0368)*** (0.0356)***	-0.0909 (0.0256)*** (0.0252)***
ADJ R-SQ	0.1314	0.1472	0.1484	0.1485	0.1338	0.1447	0.1414	0.2012	0.1657
OBS.	534	534	534	534	455	455	455	299	455
LM TEST (p-value)	1172.18 (0.0000)	648.20 (0.0000)	662.75 (0.0000)	655.72 (0.0000)	575.13 (0.0000)	562.67 (0.0000)	564.20 (0.0000)	364.49 (0.0000)	613.09 (0.0000)
HAUSMAN TEST (p-value)	5.01 (0.0252)	181.18 (0.0000)	611.77 (0.0000)	170.42 (0.0000)	76.62 (0.0000)	82.95 (0.0000)	12.22 (0.0573)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

(b) Dynamic Model

Table 6.19 displays the long-run results for human capital inequality as measured by the age at which the highest education level was completed. The validity of the models is confirmed by the test results[90] reported in Appendix A6.26, which also presents the short-run results.

Regression 1 of Appendix A6.26, which has already been presented, shows that the coefficient on the lagged dependent variable is positive and statistically significant. On adding income per capita and income inequality variables to the model, the coefficient on the lagged dependent variable is insignificant, expect for in equations 2a, 4a, 6b and 7b. Thus, the impact of lagged human capital inequality on current inequality is robust. Considering the long-run coefficients (Table 6.19), the impact of the average age at which the highest education level was completed (AMN) on inequality is not clear. Nevertheless, both the income per capita of normally working people (NMN) and income inequality among normally working people ($NGE1$) are positively associated with educational inequality. Their coefficients are also robust. The coefficients on all the control variables (population ageing (AGE), the economic activity rate of the total population ($ECACRA$) and women ($ECACRF$), the percentage of normally working respondents ($LFSTOCK$), the percentage of unemployed respondents ($UNEM$) and the percentage of inactive respondents ($INACTIVE$)) are insignificant.

[90] As in the dynamic regressions with the income distribution for the population as a whole explanatory variables, the Sargan tests accept the overidentifying restrictions in Regressions 4, 6 and 7, only when the explanatory variables are assumed to be predetermined or endogenous. The tests for serial correlation reject the absence of first-order except for equations 2c, 3c, 4c (robust and non-robust standard errors), 2b, 3b and 4b (robust standard errors). On the other hand, the tests accept the absence of second-order in all equations. Hence, there is no any equation that satisfies all the specification tests (as was the case with dynamic regressions with the income distribution for the population as a whole explanatory variables).

Table 6.19: Long Run GMM: Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

	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
AMN	-0.0036 (0.0051) *(0.0068)*	-0.0002 (0.0034) *(0.0042)*	-0.0003 (0.0048) *(0.0054)*	0.0009 (0.0022) *(0.0030)*	0.0009 (0.0016) *(0.0016)*	0.0003 (0.0017) *(0.0019)*	0.0012 (0.0020) *(0.0028)*	0.0011 (0.0015) *(0.0015)*	0.0007 (0.0017) *(0.0018)*	0.0013 (0.0020) *(0.0027)*	0.0004 (0.0016) *(0.0018)*	-0.0007 (0.0019) *(0.0024)*
NMN				0.0011 (0.0004)*** *(0.0005)*****	0.0007 (0.0003)** *(0.0004)****	0.0008 (0.0004)** *(0.0005)*	0.0010 (0.0004)*** *(0.0005)*****	0.0006 (0.0003)** *(0.0004)****	0.0007 (0.0004)* *(0.0005)*	0.0012 (0.0004)*** *(0.0005)*****	0.0006 (0.0003)** *(0.0004)****	0.0007 (0.0004) *(0.0005)*
NGE1				0.0153 (0.0160) *(0.0131)*	0.0724 (0.0158)*** *(0.0298)*****	0.0824 (0.0277)*** *(0.0351)*****	0.0164 (0.0152) *(0.0123)*	0.0721 (0.0158)*** *(0.0297)*****	0.0808 (0.0278)*** *(0.0349)*****	0.0135 (0.0154) *(0.0116)*	0.0681 (0.0161)*** *(0.0320)*****	0.0858 (0.0273)*** *(0.0379)*****
AGE							0.0008 (0.0009) *(0.0009)*	0.0006 (0.0007) *(0.0007)*	0.0004 (0.0007) *(0.0007)*	0.0008 (0.0009) *(0.0009)*	0.0006 (0.0007) *(0.0006)*	0.0003 (0.0007) *(0.0007)*
LFSTOCK										-0.0403 (0.0343) *(0.0423)*	-0.0479 (0.0359) *(0.0507)*	-0.0926 (0.0577) *(0.0693)*
ECACRA												
UNEM												
INACTIVE												
ECACRF												
OBS.	348			348			348			348		
	REGRESSION (5)			REGRESSION (6)			REGRESSION (7)					
AMN	0.0011 (0.0018) *(0.0024)*	-0.0004 (0.0019) *(0.0024)*	-0.0001 (0.0022) *(0.0024)*	0.0011 (0.0018) *(0.0025)*	0.0007 (0.0021) *(0.0024)*	-0.0003 (0.0023) *(0.0033)*	0.0012 (0.0018) *(0.0024)*	0.0002 (0.0021) *(0.0021)*	-0.0017 (0.0024) *(0.0027)*			
NMN	0.0010 (0.0005)** *(0.0005)*****	0.0005 (0.0005) *(0.0005)*	0.0008 (0.0006) *(0.0005)*	0.0011 (0.0005)** *(0.0005)*****	0.0006 (0.0006) *(0.0007)*	0.0010 (0.0006) *(0.0007)*	0.0011 (0.0005)** *(0.0005)*****	0.0003 (0.0006) *(0.0005)*	0.0003 (0.0007) *(0.0005)*			
NGE1	0.0202 (0.0176) *(0.0134)*	0.0965 (0.0265)*** *(0.0376)*****	0.0964 (0.0405)** *(0.0508)****	0.0202 (0.0169) *(0.0135)*	0.0780 (0.0247)*** *(0.0351)*****	0.0984 (0.0330)*** *(0.0406)*****	0.0205 (0.0175) *(0.0146)*	0.0627 (0.0272)** *(0.0344)****	0.0838 (0.0370)** *(0.0408)*****			
AGE	0.0008 (0.0009) *(0.0009)*	0.0006 (0.0010) *(0.0009)*	0.0005 (0.0011) *(0.0009)*	0.0008 (0.0009) *(0.0009)*	0.0004 (0.0011) *(0.0011)*	0.0003 (0.0010) *(0.0009)*	0.0007 (0.0010) *(0.0008)*	-0.0001 (0.0012) *(0.0010)*	-0.0002 (0.0012) *(0.0010)*			
LFSTOCK												
ECACRA	0.0001 (0.0005) *(0.0005)*	-0.0001 (0.0009) *(0.0010)*	0.0001 (0.0012) *(0.0018)*									
UNEM				-0.0284 (0.0502) *(0.0441)*	0.0114 (0.0744) *(0.0878)*	0.0162 (0.0968) *(0.1040)*						
INACTIVE							0.0415 (0.0420) *(0.0513)*	0.0946 (0.0743) *(0.0814)*	0.1078 (0.1014) *(0.1319)*			
ECACRF				0.0004 (0.0005) *(0.0005)*	0.0002 (0.0008) *(0.0008)*	0.0008 (0.0009) *(0.0010)*	0.0005 (0.0005) *(0.0005)*	-0.0003 (0.0008) *(0.0007)*	0.0000 (0.0012) *(0.0015)*			
OBS.	285			285			285					

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator.

6.4.3 Conclusion

Table 6.20 displays the general conclusions on the determinants of educational inequality measured either as inequality in the education level completed or as inequality in the age at which the highest education level was completed. More specifically, this table presents the sign and the robustness of educational attainment, income per capita and income inequality. First of all, the coefficients on *educational attainment* and *income per capita* are sensitive to the definition of human capital distribution. Partial conclusion 1 shows that while the impact of educational attainment on educational inequality is negative, robust and large in magnitude, the impact of income per capita on education inequality is not clear. Partial conclusion 2, on the other hand, shows that the influence of educational attainment on educational inequality is not clear, while the coefficient on income per capita is positive, statistically significant, but sensitive to the specification model. Combining both partial conclusions, and at the risk of some generalisations, the findings seem to indicate the ambiguous impact of educational attainment and income per capita on educational inequality. Nevertheless, no matter how educational and income inequalities are measured; the results show the positive and robust impact of *income inequality* on educational inequality. This finding highlight the fact that rich people have greater educational opportunities than the poor. Rich people have better job chances and greater opportunities to take up an otherwise profitable education level, if it is necessary. Moreover, the positive impact of income inequality on educational inequality most probably reflects the responsiveness of the EU labour market to differences in qualifications and skills, due to the causality effects. Education is causally related to increases in individual productivity and, therefore, in individual income. One key finding is that the coefficients on income inequality (both among the population as a whole and among normally working people) are higher when dependent variable is inequality in education level completed rather than inequality in the age at which the highest education level was completed. Moreover, the adjusted R-squared of the equations for inequality in education level completed are higher than those for the equations for inequality in age at which the highest education level was completed. What this seems to show is that the equations for the inequality in the education level completed constitute better FEs models in terms of goodness-of-fit. Finally, there is no great difference between the models for income of the population as a whole and the income of normally working people explanatory variables. The adjusted R-squared is higher in the former than in the latter models though.

Educational inequality has evolved differently in urban and rural areas. The OLS and REs results show that while inequality in the education level completed is higher in urban areas, inequality in the age at which the highest level of education was completed is lower in those areas. However, the fact that data were only available for a few regions available calls for some caution. Considering both proxies for educational inequality, the equations show that inequality is lower in the north than in the south. Finally, the results of my analysis show that the social-democratic welfare states, the mainly Protestant regions and those with Nordic family structures are among the most egalitarian.

Autoregressive models (short-run GMM regressions) highlight the persistence of educational inequality, because most people in the survey have already completed their formal studies and thus their time-series variation in education level completed is zero. However, the coefficients on the lagged age inequality are sensitive to the additional variables.

The educational inequality regressions have important policy implications. They show that improving access to education, providing a higher quality of education and generally increasing educational attainment will curb the increase in educational inequality only in such cases when the education level completed is a proxy for human capital distribution. They also indicate that income and educational inequality are connected, highlighting the responsiveness of the EU labour market to differences in qualifications and skills. Microeconomic changes in income distribution as measured by levels of inequality seem to be more important than those measured by the average income distribution.

Table 6.20: Determinants of Educational Inequality

	dependent variable										
	inequality in education level completed					**inequality in age at which the highest education level was completed**					**general conclusion**
independent variables	income for all people		income for normally working people		**partial conclusion (1)**	income for all people		income for normally working people		**partial conclusion (2)**	
	static	dynamic	static	dynamic		static	dynamic	static	dynamic		
educational attainmnet	- (rob)	- (rob)	- (rob)	- (rob)	- (rob)	+ (rob)	not clear	+ (rob)	not clear	not clear	not clear
income per capita	+ (non rob)	- (non rob)	not clear	- (non rob)	not clear	+ (non rob)	+ (non rob)	+ (non rob)	+ (rob)	+ (non rob)	not clear
income inequality	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)	+ (rob)

Note: 'not clear' means either not statistically significant coefficients in all equations or coefficients do not keep the same sign; 'robustness' means sensitivity of coefficients in terms of additional explanatory variables.

6.5 Conclusions

On the one hand, there is no great difference in the educational inequality models when the independent variable is the income of the population as a whole or the income of normally working people. On the other hand, income inequality models are sensitive to the definition of human capital variables (both educational attainment and educational inequality).

(1) The FEs for *education level completed inequality models* fit by far better than the FEs for income inequality (either for the population as a whole or for normally working people) models. The former models explain above 75.80 per cent of the variation in human capital inequality levels, while the latter explain from 0.01 to 27.04 per cent of the variation in income inequality. One reason for this may be that educational attainment explains the major part of the variation in educational inequality, while income per capita does not explain the major part of income inequality. In the former model, women's access to work access explains the largest part of variability. Considering the negative, large in magnitude and robust relationship between educational attainment and educational inequality, the average education level completed seems to play a prominent role and to be one of the most powerful instruments for reducing educational inequality. The increased opportunity to acquire higher education enables more people to improve their socioeconomic circumstances. Moreover, educational expansion and free primary and secondary education have offered educational opportunities and numerous favourable chances to both advantaged and disadvantaged groups. Considering the positive, large in magnitude and

robust relationship between women's access to work and income inequality, the impact of the increase in women's access to work has been to lessen the trend toward greater income inequality caused by aspects of social change during the period of analysis such as inflexible working conditions and arrangements, inadequate sharing of family responsibility and the lack of sufficient services such as childcare. Although women still have limited access to the labour market, men have taken on more responsibilies in care-giving and household tasks than in the past.

(2) The FEs for *inequality in the age at which the highest education level was completed models* fit slightly better than the FEs for income inequality models. The former models explain from 13.14 to 17.97 per cent of the variation in human capital inequality levels. In these static models, educational attainment explains a major part of the variation in educational inequality. Taking into account the positive, large in magnitude and robust relationship in static models between educational attainment and educational inequality, an increase in educational attainment is more likely to be a consequence of an increase in expenditure on private education rather than a consequence of an increase in educational state grants or of a decrease in tuition fees. State grants are not large enough so as to provide educational opportunities for all young people to rise to higher education levels. To put it another way, rich people are more likely to continue their studies to an older age than the poor. However, this explanation requires some caution because the relationship is not clear in the long-run models. Parenthetically, the difference in sign between the average level of human capital and inequality in human capital in both proxies is most likely a reflection of the fact that a measurement of the age at which the highest education level was completed is a broader concept of human capital. This proxy is likely to encompass experience, improved information about labour market institutions, learning-by-doing and on-the-job training, from a positive point of view, and economic inactivity and short-term unemployment, from a negative point of view.

The major conclusion of this chapter is the following. No matter how income inequality is measured and no matter how educational inequality is measured, the regression results show that the relationship between *income and educational inequality is positive and robust to the specification static and dynamic models.* On the one hand, a greater share of highly-educated workers of any age within a region may signal to employers that those with less education have a lower ability, which may also lead to larger wage differential between highly-educated and less-educated workers, and thus to greater income inequality, especially among normally working people. Based on this theory, an increase in the levels of education among the more highly-educated people tends to increase income inequality, as the imperfect competition for positions requiring advanced educational credentials leads to further increases in the wages of educated people. The human capital returns for highly-educated people are greater than those for less-educated people. Additionally, people with a very low education level (either people who have completed less than the second stage of secondary level education or people who completed their highest education level when they were young) are more likely to be unemployed. Another explanation is that the demand for unskilled labour is growing at a slower rate than the demand for skilled labour. Hence, the positive impact of educational inequality on income inequality seems to reflect the responsiveness of the EU labour market to differences in qualifications and skills. On the other hand, the higher the income inequality, the higher the human capital inequality. The most likely explanation here is that rich people have more educational opportunities than the poor. Rich people have better job chances and greater opportunities to take up even an otherwise profitable education level. Therefore, income and educational inequalities are mutually self-reinforcing processes. Human capital produces income, and vice versa. Income inequality is strongly related to educational inequality, but the scale of the effect is relatively small. Both income and human capital inequalities are likely to represent inequalities in abilities, knowledge, skills, aspirations, socioeconomic chances, opportunities, and so on. Furthermore, regional economies are internally tied to one another through income and human interdependencies, implying that they are the source of positive externalities. Those externalities are observable in diverse domains of regional economic activity, including dense knowledge and information flows, processes of learning-by-doing, business and social networks (Storper, 1997; Scott, 2002; Scott and Storper, 2003).

The static regression models reveal two distinct patterns. First, the levels of inequality have evolved differently in urban and rural areas. While urbanisation is negatively associated with income inequality for the population as a whole, it is not statistically significant for income inequality for normally working people. This most probably reflects the fact that all members of a household move to urban areas in search of better opportunities rather than normally working people alone. Additionally, the impact of urbanisation on inequality in the age at which the highest education level was completed is negative, but its impact on education level completed inequality is, surprisingly, positive. This may reflect the differences in human capital proxies. The fact that the OLS and REs models are not the most appropriate models to explain the determinants of income and human capital inequality and that data on urbanisation were only available for a few countries indicate that results should be treated with some caution. Second, the levels of inequality have also evolved differently in southern and northern areas. More specifically, inequalities in income and education are higher in the south than in the north. The FEs findings show that the impact of both urbanisation and latitude on inequalities was greater in 2000 than in 1995. This result may reveal the existence of convergence over the short period analysed. Finally, the regression results show that inequalities in income and education are lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures, such as in Swedish and Danish regions.

Most of the statistically significant coefficients indicate impacts that follow the directions suggested by the theory and previous research. As a whole, the results seem reasonable and there are socioeconomic theories in the literature that confirm the observed relationships. Microeconomic changes in income and educational distribution as measured by inequality seem to be more important than measured by those measured by average. The analysis provides useful insights for future regional and welfare policy in the EU and the goal of equalisation in income and educational opportunities and chances. Those policies should take into account the responsiveness of the EU labour market to differences in qualifications and skills.

Appendix A6

Appendix A6.1: Descriptive Statistics of the ECHP Dataset

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 A6.2: Standardised Coefficients

Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

DEPENDENT VARIABLE: IGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
IMN	-0.6514	-0.3659	-0.3360	-0.0449	-0.1675	-0.0845	-0.1105	-0.2136	0.0526
EMN		-0.5168	-0.5331	-0.1467	0.0171	0.0877	0.1149	0.1418	0.0624
EGE1		-0.1598	-0.1185	0.2067	0.2553	0.2854	0.2460	0.1985	0.1545
AGE			-0.1662	-0.2178	-0.1712	-0.0964	-0.1661	-0.0537	-0.0945
LFSTOCK				-0.5644					
ECACRA					-0.5712				
UNEM						0.0531		0.1887	0.0501
INACTIVE							0.1974		
ECACRF						-0.6773	-0.5612	-0.5035	-0.4929
URBANDPAV (fixed)								-0.1148	
LAT (fixed)									-0.4330

Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

DEPENDENT VARIABLE: IGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
IMN	-0.6514	-0.4022	-0.3614	-0.0378	-0.2365	-0.1451	-0.1440	-0.1390	0.1136
AMN		-0.2659	-0.3197	-0.3275	-0.2551	-0.2342	-0.1667	-0.1475	-0.1322
AGE1		0.3071	0.3714	0.3467	0.1134	0.0705	0.0865	0.1007	-0.0356
AGE			-0.1582	-0.2081	-0.1655	-0.0934	-0.1735	-0.0456	-0.0973
LFSTOCK				-0.5248					
ECACRA					-0.4921				
UNEM						0.0833		0.2309	0.0656
INACTIVE							0.1887		
ECACRF						-0.5793	-0.4931	-0.4093	-0.4959
URBANDPAV (fixed)								-0.0999	
LAT (fixed)									-0.5164

Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

DEPENDENT VARIABLE: NGE1						
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6
NMN	-0.3975	-0.0187	-0.0196	-0.0309	-0.1803	0.1063
EMN		0.0020	0.0023	0.3836	0.1752	0.3665
EGE1		0.5368	0.5340	0.6557	0.3556	0.4877
AGE			0.0118	0.0515	0.1522	0.0567
ECACRF				-0.3757	-0.1102	-0.0985
URBANDPAV (fixed)					-0.0883	
LAT (fixed)						-0.5556

Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

DEPENDENT VARIABLE: NGE1						
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6
NMN	-0.3975	-0.0775	-0.0936	-0.1570	-0.0099	0.0531
AMN		-0.4638	-0.4357	-0.3871	-0.4010	-0.2811
AGE1		0.3046	0.2712	0.1069	0.1635	-0.0071
AGE			0.0997	0.0900	0.1678	0.0935
ECACRF				-0.1016	-0.0138	0.0571
URBANDPAV (fixed)					-0.0950	
LAT (fixed)						-0.5251

Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

DEPENDENT VARIABLE: EGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
EMN	-0.8691	-0.7804	-0.7592	-0.7572	-0.8159	-0.7526	-0.8202	-0.7740	-0.7383
IMN		-0.1760	-0.1777	-0.2474	-0.1649	-0.2510	-0.1669	-0.3523	-0.2079
IGE1		-0.0732	-0.0566	0.1238	0.1893	0.2424	0.2361	0.1737	0.1656
AGE			0.0512	0.0994	0.0575	-0.0004	0.0265	0.0240	-0.0067
LFSTOCK				0.2998					
ECACRA					0.3385				
UNEM						-0.1654		-0.0269	-0.1590
INACTIVE							0.0164		
ECACRF						0.3214	0.3902	0.4541	0.3250
URBANDPAV (fixed)								0.1452	
LAT (fixed)									-0.1384

Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

DEPENDENT VARIABLE: EGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
EMN	-0.8691	-0.6651	-0.6566	-0.7583	-0.8174	-0.7903	-0.8179	-0.7632	-0.7648
NMN		-0.1849	-0.1867	-0.2046	-0.1497	-0.1964	-0.1537	-0.3286	-0.1653
NGE1		0.1569	0.1543	0.1755	0.1816	0.1745	0.1968	0.0935	0.1379
AGE			0.0487	0.0549	0.0155	-0.0266	-0.0149	0.0008	-0.0250
LFSTOCK				0.2083					
ECACRA					0.2250				
UNEM						-0.1072		0.0374	-0.1140
INACTIVE							0.0294		
ECACRF						0.1776	0.2550	0.3219	0.2223
URBANDPAV (fixed)								0.1315	
LAT (fixed)									-0.1293

Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

DEPENDENT VARIABLE: AGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
AMN	0.2172	0.5879	0.6144	0.6334	0.6107	0.6715	0.5680	0.4208	0.6563
IMN		-0.6288	-0.5922	-0.6405	-0.6115	-0.6377	-0.6151	-0.5874	-0.4760
IGE1		0.2588	0.2943	0.4032	0.1505	0.1102	0.1356	0.1673	-0.0755
AGE			0.2092	0.2380	0.1517	0.1307	0.2379	0.0870	0.1049
LFSTOCK				0.1827					
ECACRA					-0.1361				
UNEM						-0.1244		-0.2575	-0.1137
INACTIVE							-0.2449		
ECACRF						-0.2467	-0.3301	-0.3696	-0.2883
URBANDPAV (fixed)								-0.0659	
LAT (fixed)									-0.3100

Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

DEPENDENT VARIABLE: AGE1									
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9
AMN	0.2172	0.5956	0.6022	0.6028	0.5960	0.6507	0.5791	0.4293	0.6582
NMN		-0.6768	-0.6728	-0.5902	-0.5526	-0.5524	-0.5356	-0.5388	-0.4255
NGE1		0.2081	0.1796	0.1529	0.0855	0.0531	0.0670	0.0803	-0.0122
AGE			0.1472	0.1305	0.1019	0.1163	0.1886	0.0631	0.1119
LFSTOCK				-0.1937					
ECACRA					-0.3454				
UNEM						-0.0860		-0.1834	-0.1042
INACTIVE							-0.1735		
ECACRF						-0.4340	-0.5028	-0.5342	-0.3437
URBANDPAV (fixed)								-0.0787	
LAT (fixed)									-0.2812

Appendix A6.3: OLS: Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IMN	-0.0253 (0.0012)*** (0.0014)***	-0.0140 (0.0018)*** (0.0021)***	-0.0129 (0.0018)*** (0.0020)***	-0.0017 (0.0016) (0.0018)	-0.0065 (0.0015)*** (0.0016)***	-0.0033 (0.0015)** (0.0017)*	-0.0043 (0.0014)*** (0.0014)***	-0.0076 (0.0024)*** (0.0028)***	0.0020 (0.0014) (0.0015)	0.0072 (0.0018)*** (0.0021)***	0.0005 (0.0015) (0.0017)	0.0084 (0.0018)*** (0.0020)***
EMN		-0.2817 (0.0355)*** (0.0304)***	-0.2906 (0.0347)*** (0.0285)***	-0.0800 (0.0312)** (0.0263)***	0.0097 (0.0331) (0.0315)	0.0498 (0.0298)* (0.0288)*	0.0652 (0.0295)** (0.0286)**	0.0710 (0.0375)* (0.0381)*	0.0354 (0.0263) (0.0237)	0.0309 (0.0338) (0.0358)	0.1064 (0.0340)*** (0.0372)***	0.0381 (0.0283) (0.0296)
EGE1		-0.0556 (0.0210)*** (0.0199)***	-0.0412 (0.0206)*** (0.0179)***	0.0719 (0.0183)*** (0.0167)***	0.0961 (0.0189)*** (0.0181)***	0.1074 (0.0175)*** (0.0166)***	0.0926 (0.0166)*** (0.0152)***	0.0700 (0.0217)*** (0.0185)***	0.0582 (0.0160)*** (0.0141)***	0.0887 (0.0187)*** (0.0192)***	0.1483 (0.0188)*** (0.0198)***	0.0935 (0.0164)*** (0.0173)***
AGE			-0.0130 (0.0023)*** (0.0024)***	-0.0170 (0.0019)*** (0.0019)***	-0.0138 (0.0019)*** (0.0018)***	-0.0078 (0.0018)*** (0.0018)***	-0.0134 (0.0020)*** (0.0022)***	-0.0041 (0.0023)* (0.0022)*	-0.0076 (0.0016)*** (0.0015)***	-0.0082 (0.0017)*** (0.0017)***	-0.0113 (0.0018)*** (0.0017)***	-0.0077 (0.0017)*** (0.0016)***
LFSTOCK				-1.1632 (0.0693)*** (0.0676)***								
ECACRA					-0.0134 (0.0008)*** (0.0007)***							
UNEM						0.2519 (0.1304)* (0.1352)*		0.8557 (0.2080)*** (0.1794)***	0.2375 (0.1150)** (0.1190)**	0.4602 (0.1410)*** (0.1380)***	0.3112 (0.1384)** (0.1431)**	0.5367 (0.1264)*** (0.1362)***
INACTIVE							0.4937 (0.1052)*** (0.1141)***					
ECACRF						-0.0116 (0.0006)*** (0.0005)***	-0.0096 (0.0007)*** (0.0008)***	-0.0083 (0.0010)*** (0.0009)***	-0.0084 (0.0006)*** (0.0006)***	-0.0085 (0.0007)*** (0.0007)***	-0.0104 (0.0006)*** (0.0006)***	-0.0082 (0.0007)*** (0.0007)***
URBANDPAV (fixed)								-0.0736 (0.0215)*** (0.0211)***				
LAT (fixed)									-0.0102 (0.0008)*** (0.0009)***			
DWSLIB										0.0356 (0.0185)* (0.0166)**		
DWSCORP										0.0374 (0.0169)** (0.0154)**		
DWSRES										0.1814 (0.0261)*** (0.0291)***		
DRLCATH											0.0408 (0.0109)*** (0.0112)***	
DRLORTH											0.1584 (0.0196)*** (0.0179)***	
DRLANGL											-0.0104 (0.0122) (0.0127)	
DFNORD												-0.0402 (0.0163)** (0.0145)***
DFSC												0.1566 (0.0147)*** (0.0179)***
ADJ R-SQ	0.4233	0.4890	0.5144	0.6709	0.7139	0.7674	0.7755	0.7672	0.8192	0.8022	0.7978	0.8097
OBS.	604	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.4: OLS: Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IMN	-0.0253 (0.0012)*** (0.0014)***	-0.0152 (0.0019)*** (0.0022)***	-0.0137 (0.0018)*** (0.0021)***	-0.0014 (0.0017) (0.0020)	-0.0091 (0.0017)*** (0.0021)***	-0.0056 (0.0017)*** (0.0020)***	-0.0055 (0.0016)*** (0.0020)***	-0.0049 (0.0022)** (0.0025)*	0.0044 (0.0016)*** (0.0019)**	0.0040 (0.0018)** (0.0022)*	-0.0009 (0.0017) (0.0021)	0.0038 (0.0018)** (0.0021)*
AMN		-0.0156 (0.0025)*** (0.0027)***	-0.0187 (0.0025)*** (0.0027)***	-0.0192 (0.0020)*** (0.0023)***	-0.0145 (0.0021)*** (0.0023)***	-0.0133 (0.0022)*** (0.0024)***	-0.0095 (0.0019)*** (0.0022)***	-0.0165 (0.0049)*** (0.0050)***	-0.0075 (0.0019)*** (0.0019)***	-0.0069 (0.0027)** (0.0025)***	-0.0206 (0.0028)*** (0.0029)***	-0.0033 (0.0022) (0.0021)
AGE1		2.1221 (0.3137)*** (0.3680)***	2.5662 (0.3185)*** (0.3591)***	2.3953 (0.2586)*** (0.3150)***	0.8442 (0.3023)*** (0.3711)**	0.5246 (0.2801)* (0.3323)	0.6435 (0.2791)** (0.3453)*	0.6948 (0.3111)** (0.3442)**	-0.2652 (0.2415) (0.2581)	-1.6838 (0.3448)*** (0.3325)***	0.7427 (0.2799)*** (0.3364)**	-1.4909 (0.3203)*** (0.3279)***
AGE			-0.0119 (0.0023)*** (0.0025)***	-0.0157 (0.0019)*** (0.0019)***	-0.0129 (0.0020)*** (0.0018)***	-0.0073 (0.0019)*** (0.0018)***	-0.0135 (0.0022)*** (0.0024)***	-0.0035 (0.0023) (0.0022)	-0.0076 (0.0016)*** (0.0015)***	-0.0064 (0.0018)*** (0.0016)***	-0.0110 (0.0019)*** (0.0019)***	-0.0050 (0.0018)*** (0.0017)***
LFSTOCK				-1.0505 (0.0633)*** (0.0585)***								
ECACRA					-0.0120 (0.0008)*** (0.0007)***							
UNEM						0.3711 (0.1504)** (0.1418)***		1.0474 (0.2125)*** (0.1693)***	0.2921 (0.1261)** (0.1181)**	0.5806 (0.1376)*** (0.1317)***	0.4357 (0.1430)*** (0.1389)***	0.6547 (0.1387)*** (0.1344)***
INACTIVE							0.4670 (0.1135)*** (0.1270)***					
ECACRF						-0.0105 (0.0007)*** (0.0006)***	-0.0089 (0.0008)*** (0.0008)***	-0.0067 (0.0010)*** (0.0008)***	-0.0090 (0.0006)*** (0.0006)***	-0.0070 (0.0007)*** (0.0007)***	-0.0083 (0.0007)*** (0.0007)***	-0.0077 (0.0007)*** (0.0006)***
URBANDPAV (fixed)								-0.0641 (0.0212)*** (0.0215)***				
LAT (fixed)									-0.0127 (0.0009)*** (0.0010)***			
DWSLIB										0.0689 (0.0309)** (0.0166)***		
DWSCORP										0.1108 (0.0304)*** (0.0171)***		
DWSRES										0.3012 (0.0418)*** (0.0350)***		
DRLCATH											0.0098 (0.0132) (0.0122)	
DRLORTH											0.0823 (0.0224)*** (0.0196)***	
DRLANGL											-0.0581 (0.0175)*** (0.0166)***	
DFNORD												-0.0914 (0.0298)*** (0.0152)***
DFSC												0.2001 (0.0196)*** (0.0199)***
ADJ R-SQ	0.4233	0.5177	0.5396	0.6970	0.7108	0.7617	0.7672	0.7686	0.8328	0.8066	0.7855	0.8061
OBS.	604	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.5: OLS: Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NMN	-0.0068 (0.0006)*** (0.0008)***	-0.0003 (0.0008) (0.0009)	-0.0003 (0.0008) (0.0009)	-0.0005 (0.0008) (0.0009)	-0.0027 (0.0016)* (0.0019)	0.0018 (0.0008)** (0.0009)*	0.0034 (0.0010)*** (0.0011)***	0.0017 (0.0008)** (0.0010)*	0.0039 (0.0009)*** (0.0011)***
EMN		0.0006 (0.0198) (0.0180)	0.0006 (0.0198) (0.0180)	0.1061 (0.0241)*** (0.0262)***	0.0404 (0.0313) (0.0298)	0.1013 (0.0224)*** (0.0232)***	0.0435 (0.0259)* (0.0287)	0.1008 (0.0263)*** (0.0297)***	0.0626 (0.0226)*** (0.0248)**
EGE1		0.0949 (0.0129)*** (0.0134)***	0.0944 (0.0130)*** (0.0140)***	0.1203 (0.0138)*** (0.0155)***	0.0578 (0.0184)*** (0.0177)***	0.0895 (0.0133)*** (0.0139)***	0.0710 (0.0152)*** (0.0168)***	0.1235 (0.0151)*** (0.0179)***	0.0791 (0.0131)*** (0.0142)***
AGE			0.0005 (0.0014) (0.0013)	0.0020 (0.0014) (0.0014)	0.0053 (0.0018)*** (0.0016)***	0.0022 (0.0013)* (0.0013)*	0.0026 (0.0013)** (0.0013)*	-0.0010 (0.0014) (0.0013)	0.0026 (0.0013)** (0.0013)**
ECACRF				-0.0031 (0.0004)*** (0.0005)***	-0.0008 (0.0006) (0.0006)	-0.0008 (0.0005)* (0.0005)	0.0007 (0.0006) (0.0006)	-0.0019 (0.0004)*** (0.0005)***	0.0011 (0.0005)** (0.0005)**
URBANDPAV (fixed)					-0.0261 (0.0181) (0.0172)				
LAT (fixed)						-0.0064 (0.0007)*** (0.0008)***			
DWSLIB							0.1068 (0.0134)*** (0.0102)***		
DWSCORP							0.0995 (0.0133)*** (0.0099)***		
DWSRES							0.1945 (0.0201)*** (0.0187)***		
DRLCATH								0.0352 (0.0086)*** (0.0086)***	
DRLORTH								0.1528 (0.0152)*** (0.0155)***	
DRLANGL								0.0212 (0.0088)** (0.0093)**	
DFNORD									-0.1054 (0.0124)*** (0.0087)***
DFSC									0.1061 (0.0114)*** (0.0114)***
ADJ R-SQ	0.1566	0.2974	0.2963	0.3557	0.2191	0.4358	0.4512	0.4556	0.4763
OBS.	604	596	596	513	299	513	513	513	513

Appendix A6.6: OLS: Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NMN	-0.0068 (0.0006)*** *(0.0008)* ***	-0.0013 (0.0009) *(0.0012)*	-0.0015 (0.0009)* *(0.0012)*	-0.0026 (0.0010)** *(0.0013)* *	-0.0001 (0.0014) *(0.0017)*	0.0009 (0.0010) *(0.0014)*	0.0012 (0.0011) *(0.0014)*	0.0003 (0.0010) *(0.0014)*	0.0013 (0.0010) *(0.0013)*
AMN		-0.0134 (0.0014)*** *(0.0014)* ***	-0.0126 (0.0014)*** *(0.0015)* ***	-0.0104 (0.0016)*** *(0.0017)* ***	-0.0206 (0.0039)*** *(0.0038)* ***	-0.0075 (0.0015)*** *(0.0015)* ***	-0.0043 (0.0022)** *(0.0022)* *	-0.0144 (0.0020)*** *(0.0021)* ***	-0.0020 (0.0017) *(0.0017)*
AGE1		1.0358 (0.1730)*** *(0.1902)* ***	0.9223 (0.1772)*** *(0.1977)* ***	0.3753 (0.2254)* *(0.2553)*	0.5198 (0.2541)** *(0.2737)* *	-0.0248 (0.2188) *(0.2209)*	-0.9961 (0.2899)*** *(0.2858)* ***	0.7272 (0.2265)*** *(0.2783)* ***	-1.0214 (0.2650)*** *(0.2587)* ***
AGE			0.0037 (0.0014)*** *(0.0013)* ***	0.0033 (0.0015)** *(0.0015)* **	0.0059 (0.0018)*** *(0.0016)* ***	0.0034 (0.0014)** *(0.0014)* **	0.0038 (0.0014)*** *(0.0014)* ***	-0.0003 (0.0015) *(0.0016)*	0.0043 (0.0014)*** *(0.0014)* ***
ECACRF				-0.0009 (0.0005)* *(0.0004)* *	-0.0001 (0.0006) *(0.0005)*	0.0005 (0.0005) *(0.0005)*	0.0014 (0.0006)** *(0.0006)* **	0.0007 (0.0005) *(0.0005)*	0.0013 (0.0005)*** *(0.0005)* ***
URBANDPAV (fixed)					-0.0281 (0.0174) *(0.0171)*				
LAT (fixed)						-0.0061 (0.0008)*** *(0.0009)* ***			
DWSLIB							0.0865 (0.0257)*** *(0.0125)* ***		
DWSCORP							0.1034 (0.0252)*** *(0.0110)* ***		
DWSRES							0.2192 (0.0342)*** *(0.0275)* ***		
DRLCATH								0.0026 (0.0105) *(0.0101)*	
DRLORTH								0.0891 (0.0180)*** *(0.0189)* ***	
DRLANGL								-0.0289 (0.0139)** *(0.0144)* **	
DFNORD									-0.0991 (0.0242)*** *(0.0091)* ***
DFSC									0.1301 (0.0153)*** *(0.0142)* ***
ADJ R-SQ	0.1566	0.3034	0.3113	0.3143	0.2616	0.3913	0.3878	0.3842	0.4112
OBS.	604	534	534	455	299	455	455	455	455

Appendix A6.7: OLS: Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EMN	-1.3612 (0.0318)*** (0.0467)***	-1.2223 (0.0525)*** (0.0589)***	-1.1891 (0.0540)*** (0.0590)***	-1.1859 (0.0497)*** (0.0540)***	-1.2297 (0.0523)*** (0.0628)***	-1.1343 (0.0530)*** (0.0584)***	-1.2362 (0.0540)*** (0.0676)***	-1.0990 (0.0765)*** (0.0800)***	-1.1127 (0.0529)*** (0.0580)***	-1.3622 (0.0501)*** (0.0516)***	-1.2859 (0.0510)*** (0.0497)***	-1.1899 (0.0529)*** (0.0571)***
IMN		-0.0194 (0.0036)*** (0.0031)***	-0.0195 (0.0036)*** (0.0031)***	-0.0272 (0.0034)*** (0.0031)***	-0.0170 (0.0035)*** (0.0030)***	-0.0259 (0.0036)*** (0.0034)***	-0.0172 (0.0035)*** (0.0031)***	-0.0355 (0.0061)*** (0.0056)***	-0.0214 (0.0038)*** (0.0034)***	-0.0075 (0.0044)* (0.0047)	-0.0207 (0.0033)*** (0.0038)***	-0.0256 (0.0046)*** (0.0048)***
IGE1		-0.2104 (0.0795)*** (0.0790)***	-0.1627 (0.0814)** (0.0740)**	0.3557 (0.0904)*** (0.0832)***	0.5029 (0.0991)*** (0.0844)***	0.6440 (0.1050)*** (0.0861)***	0.6272 (0.1123)*** (0.0997)***	0.4926 (0.1528)*** (0.1372)***	0.4398 (0.1208)*** (0.1004)***	0.4814 (0.1016)*** (0.0923)***	0.7405 (0.0940)*** (0.0732)***	0.6511 (0.1139)*** (0.1008)***
AGE			0.0115 (0.0046)** (0.0050)**	0.0223 (0.0044)*** (0.0045)***	0.0123 (0.0046)*** (0.0049)**	-0.0001 (0.0045) (0.0051)	0.0057 (0.0054) (0.0058)	0.0052 (0.0061) (0.0076)	-0.0014 (0.0045) (0.0050)	0.0111 (0.0041)*** (0.0052)**	0.0163 (0.0041)*** (0.0049)***	0.0047 (0.0045) (0.0052)
LFSTOCK				1.7752 (0.1724)*** (0.1759)***								
ECACRA					0.0211 (0.0021)*** (0.0021)***							
UNEM						-2.0828 (0.3068)*** (0.3052)***		-0.3464 (0.5673) (0.7354)	-2.0025 (0.3048)*** (0.2980)***	0.1922 (0.3317) (0.4129)	-0.3720 (0.3104) (0.3817)	-1.5483 (0.3323)*** (0.3708)***
INACTIVE							0.1087 (0.2796) (0.2723)					
ECACRF						0.0146 (0.0018)*** (0.0016)***	0.0177 (0.0020)*** (0.0018)***	0.0212 (0.0026)*** (0.0022)***	0.0147 (0.0017)*** (0.0016)***	0.0166 (0.0018)*** (0.0018)***	0.0142 (0.0015)*** (0.0015)***	0.0186 (0.0019)*** (0.0018)***
URBANDPAV (fixed)								0.2642 (0.0561)*** (0.0440)***				
LAT (fixed)									-0.0087 (0.0026)*** (0.0023)***			
DWSLIB										0.3650 (0.0401)*** (0.0348)***		
DWSCORP										0.1249 (0.0391)*** (0.0326)***		
DWSRES										0.2557 (0.0626)*** (0.0636)***		
DRLCATH											0.0126 (0.0246) (0.0216)	
DRLORTH											-0.1580 (0.0461)*** (0.0407)***	
DRLANGL											0.2663 (0.0246)*** (0.0211)***	
DFNORD												-0.2059 (0.0423)*** (0.0334)***
DFSC												-0.0158 (0.0429) (0.0451)
ADJ R-SQ	0.7549	0.7658	0.7678	0.8029	0.7878	0.8024	0.7845	0.7963	0.8063	0.8480	0.8569	0.8123
OBS.	596	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.8: OLS: Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EMN	-1.3612 (0.0318)*** (0.0467)***	-1.0417 (0.0426)*** (0.0439)***	-1.0284 (0.0427)*** (0.0447)***	-1.1876 (0.0432)*** (0.0495)***	-1.2320 (0.0481)*** (0.0589)***	-1.1911 (0.0495)*** (0.0557)***	-1.2327 (0.0507)*** (0.0637)***	-1.0838 (0.0754)*** (0.0736)***	-1.1527 (0.0504)*** (0.0544)***	-1.3747 (0.0473)*** (0.0520)***	-1.3245 (0.0483)*** (0.0502)***	-1.2316 (0.0503)*** (0.0567)***
NMN		-0.0176 (0.0025)*** (0.0023)***	-0.0178 (0.0025)*** (0.0023)***	-0.0195 (0.0023)*** (0.0022)***	-0.0136 (0.0024)*** (0.0023)***	-0.0179 (0.0026)*** (0.0026)***	-0.0140 (0.0025)*** (0.0024)***	-0.0301 (0.0047)*** (0.0042)***	-0.0151 (0.0027)*** (0.0025)***	-0.0056 (0.0031)* (0.0036)	-0.0155 (0.0024)*** (0.0030)***	-0.0175 (0.0032)*** (0.0035)***
NGE1		0.8873 (0.1203)*** (0.1066)***	0.8729 (0.1198)*** (0.1103)***	0.9928 (0.1123)*** (0.1002)***	0.9899 (0.1222)*** (0.1097)***	0.9514 (0.1260)*** (0.1077)***	1.0727 (0.1261)*** (0.1166)***	0.5754 (0.1803)*** (0.1643)***	0.7519 (0.1383)*** (0.1316)***	0.5903 (0.1251)*** (0.1306)***	0.9599 (0.1168)*** (0.1087)***	0.8194 (0.1403)*** (0.1394)***
AGE			0.0109 (0.0042)** (0.0046)**	0.0123 (0.0039)*** (0.0040)***	0.0033 (0.0042) (0.0044)	-0.0057 (0.0044) (0.0048)	-0.0032 (0.0050) (0.0052)	0.0002 (0.0061) (0.0079)	-0.0053 (0.0043) (0.0047)	0.0058 (0.0040) (0.0053)	0.0096 (0.0040)** (0.0047)**	-0.0023 (0.0044) (0.0051)
LFSTOCK				1.2336 (0.1291)*** (0.1217)***								
ECACRA					0.0140 (0.0016)*** (0.0017)***							
UNEM						-1.3506 (0.3049)*** (0.3012)***		0.4806 (0.5486) (0.6450)	-1.4358 (0.3029)*** (0.3035)***	0.4535 (0.3156) (0.3882)	0.1802 (0.3011) (0.3675)	-1.0256 (0.3181)*** (0.3401)***
INACTIVE							0.1956 (0.2646) (0.2461)					
ECACRF						0.0081 (0.0014)*** (0.0013)***	0.0116 (0.0017)*** (0.0016)***	0.0150 (0.0023)*** (0.0021)***	0.0101 (0.0015)*** (0.0015)***	0.0117 (0.0017)*** (0.0019)***	0.0069 (0.0013)*** (0.0012)***	0.0109 (0.0019)*** (0.0019)***
URBANDPAV (fixed)								0.2392 (0.0551)*** (0.0441)***				
LAT (fixed)									-0.0081 (0.0024)*** (0.0024)***			
DWSLIB										0.3196 (0.0423)*** (0.0404)***		
DWSCORP										0.0841 (0.0410)** (0.0371)**		
DWSRES										0.2229 (0.0640)*** (0.0715)***		
DRLCATH											0.0123 (0.0245) (0.0214)	
DRLORTH											-0.1770 (0.0464)*** (0.0418)***	
DRLANGL											0.2454 (0.0249)*** (0.0214)***	
DFNORD												-0.1508 (0.0447)*** (0.0380)***
DFSC												0.0046 (0.0406) (0.0453)
ADJ R-SQ	0.7549	0.7947	0.7966	0.8236	0.8033	0.8091	0.8019	0.7986	0.8129	0.8481	0.8583	0.8132
OBS.	596	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.9: OLS: Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AMN	0.0018 (0.0004)*** *(0.0003)****	0.0050 (0.0003)*** *(0.0002)****	0.0052 (0.0002)*** *(0.0002)****	0.0054 (0.0002)*** *(0.0002)****	0.0047 (0.0003)*** *(0.0002)****	0.0051 (0.0003)*** *(0.0003)****	0.0043 (0.0003)*** *(0.0002)****	0.0068 (0.0008)*** *(0.0009)****	0.0050 (0.0003)*** *(0.0003)****	0.0047 (0.0003)*** *(0.0002)****	0.0051 (0.0004)*** *(0.0004)****	0.0046 (0.0002)*** *(0.0002)****
IMN		-0.0034 (0.0002)*** *(0.0002)****	-0.0032 (0.0002)*** *(0.0002)****	-0.0035 (0.0002)*** *(0.0002)****	-0.0031 (0.0002)*** *(0.0002)****	-0.0033 (0.0002)*** *(0.0003)****	-0.0032 (0.0002)*** *(0.0002)****	-0.0030 (0.0004)*** *(0.0004)****	-0.0024 (0.0003)*** *(0.0003)****	0.0001 (0.0002) *(0.0002)*	-0.0034 (0.0002)*** *(0.0003)****	-0.0002 (0.0003) *(0.0003)*
IGE1		0.0375 (0.0055)*** *(0.0048)****	0.0426 (0.0053)*** *(0.0044)****	0.0583 (0.0063)*** *(0.0052)****	0.0202 (0.0072)*** *(0.0077)****	0.0148 (0.0079)* *(0.0086)***	0.0182 (0.0079)** *(0.0087)***	0.0243 (0.0109)** *(0.0108)***	-0.0101 (0.0092) *(0.0102)*	-0.0302 (0.0062)*** *(0.0060)****	0.0210 (0.0079)*** *(0.0086)***	-0.0311 (0.0067)*** *(0.0066)****
AGE			0.0023 (0.0003)*** *(0.0003)****	0.0026 (0.0003)*** *(0.0003)****	0.0016 (0.0003)*** *(0.0004)****	0.0014 (0.0003)*** *(0.0004)****	0.0025 (0.0004)*** *(0.0005)****	0.0010 (0.0004)** *(0.0005)**	0.0011 (0.0003)*** *(0.0004)****	0.0009 (0.0002)*** *(0.0003)****	0.0019 (0.0003)*** *(0.0004)****	0.0010 (0.0003)*** *(0.0003)****
LFSTOCK				0.0529 (0.0120)*** *(0.0106)****								
ECACRA					-0.0004 (0.0002)*** *(0.0002)***							
UNEM						-0.0744 (0.0252)*** *(0.0257)****		-0.1693 (0.0401)*** *(0.0385)****	-0.0680 (0.0246)*** *(0.0256)****	0.0241 (0.0188) *(0.0178)*	-0.0771 (0.0240)*** *(0.0251)****	0.0300 (0.0205) *(0.0181)**
INACTIVE							-0.0814 (0.0191)*** *(0.0191)****					
ECACRF						-0.0006 (0.0001)*** *(0.0002)****	-0.0008 (0.0002)*** *(0.0002)****	-0.0009 (0.0002)*** *(0.0002)****	-0.0007 (0.0001)*** *(0.0002)****	-0.0002 (0.0001) *(0.0001)*	-0.0005 (0.0001)*** *(0.0002)****	-0.0002 (0.0001)* *(0.0001)**
URBANDP AV (fixed)								-0.0061 (0.0040) *(0.0043)*				
LAT (fixed)									-0.0010 (0.0002)*** *(0.0002)****			
DWSLIB										0.0217 (0.0040)*** *(0.0050)****		
DWSCORP										0.0210 (0.0040)*** *(0.0050)****		
DWSRES										0.0670 (0.0050)*** *(0.0058)****		
DRLCATH											0.0043 (0.0022)* *(0.0018)***	
DRLORTH											-0.0148 (0.0038)*** *(0.0030)****	
DRLANGL											0.0013 (0.0030) *(0.0027)*	
DFNORD												-0.0196 (0.0042)*** *(0.0051)****
DFSC												0.0420 (0.0024)*** *(0.0032)****
ADJ R-SQ	0.0454	0.5936	0.6352	0.6476	0.6162	0.6273	0.6348	0.6158	0.6455	0.8078	0.6645	0.7761
OBS.	534	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.10: OLS: Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AMN	0.0018 (0.0004)*** (0.0003)***	0.0051 (0.0003)*** (0.0002)***	0.0051 (0.0003)*** (0.0002)***	0.0051 (0.0003)*** (0.0002)***	0.0046 (0.0003)*** (0.0002)***	0.0050 (0.0003)*** (0.0003)***	0.0044 (0.0003)*** (0.0002)***	0.0070 (0.0008)*** (0.0010)***	0.0050 (0.0003)*** (0.0002)***	0.0050 (0.0003)*** (0.0002)***	0.0048 (0.0004)*** (0.0004)***	0.0048 (0.0002)*** (0.0002)***
NMN		-0.0033 (0.0002)*** (0.0002)***	-0.0032 (0.0002)*** (0.0002)***	-0.0029 (0.0002)*** (0.0002)***	-0.0026 (0.0002)*** (0.0002)***	-0.0026 (0.0002)*** (0.0002)***	-0.0025 (0.0002)*** (0.0002)***	-0.0025 (0.0003)*** (0.0003)***	-0.0020 (0.0002)*** (0.0002)***	-0.0002 (0.0002) (0.0002)	-0.0027 (0.0002)*** (0.0002)***	-0.0005 (0.0002)** (0.0002)**
NGE1		0.0612 (0.0102)*** (0.0097)***	0.0528 (0.0101)*** (0.0101)***	0.0450 (0.0099)*** (0.0102)***	0.0244 (0.0099)** (0.0106)**	0.0151 (0.0098) (0.0107)	0.0191 (0.0098)* (0.0105)*	0.0253 (0.0131)* (0.0130)*	-0.0035 (0.0102) (0.0106)	-0.0259 (0.0075)*** (0.0080)***	0.0299 (0.0097)*** (0.0110)***	-0.0315 (0.0082)*** (0.0089)***
AGE			0.0016 (0.0003)*** (0.0004)***	0.0014 (0.0003)*** (0.0004)***	0.0011 (0.0003)*** (0.0004)***	0.0012 (0.0003)*** (0.0004)***	0.0020 (0.0003)*** (0.0005)***	0.0007 (0.0004) (0.0005)	0.0012 (0.0003)*** (0.0004)***	0.0012 (0.0002)*** (0.0003)***	0.0017 (0.0003)*** (0.0004)***	0.0013 (0.0002)*** (0.0003)***
LFSTOCK				-0.0561 (0.0097)*** (0.0090)***								
ECACRA					-0.0011 (0.0001)*** (0.0001)***							
UNEM						-0.0514 (0.0245)** (0.0258)**		-0.1206 (0.0385)*** (0.0400)***	-0.0623 (0.0239)*** (0.0261)**	0.0014 (0.0182) (0.0170)	-0.0497 (0.0230)** (0.0247)**	0.0041 (0.0195) (0.0173)
INACTIVE							-0.0577 (0.0186)*** (0.0189)***					
ECACRF						-0.0011 (0.0001)*** (0.0001)***	-0.0012 (0.0001)*** (0.0001)***	-0.0013 (0.0002)*** (0.0002)***	-0.0008 (0.0001)*** (0.0001)***	0.0001 (0.0001) (0.0001)	-0.0009 (0.0001)*** (0.0001)***	0.0000 (0.0001) (0.0001)
URBANDPAV (fixed)								-0.0073 (0.0039)* (0.0041)*				
LAT (fixed)									-0.0009 (0.0002)*** (0.0002)***			
DWSLIB										0.0218 (0.0041)*** (0.0050)***		
DWSCORP										0.0202 (0.0040)*** (0.0049)***		
DWSRES										0.0633 (0.0050)*** (0.0056)***		
DRLCATH											0.0040 (0.0022)* (0.0018)*	
DRLORTH											-0.0172 (0.0037)*** (0.0030)***	
DRLANGL											-0.0005 (0.0029) (0.0026)	
DFNORD												-0.0194 (0.0043)*** (0.0049)***
DFSC												0.0386 (0.0023)*** (0.0029)***
ADJ R-SQ	0.0454	0.5242	0.5439	0.5705	0.6180	0.6341	0.6382	0.6213	0.6542	0.8033	0.6780	0.7755
OBS.	534	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.11: REs: Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IMN	-0.0036 (0.0011)*** (0.0013)***	-0.0012 (0.0014) (0.0015)	-0.0009 (0.0015) (0.0016)	0.0008 (0.0015) (0.0015)	-0.0001 (0.0015) (0.0015)	0.0020 (0.0015) (0.0015)***	0.0014 (0.0015) (0.0015)	0.0020 (0.0017) (0.0017)	0.0042 (0.0014)*** (0.0014)***	0.0053 (0.0015)*** (0.0015)***	0.0030 (0.0015)** (0.0014)**	0.0054 (0.0015)*** (0.0015)***
EMN		0.0371 (0.0304) (0.0339)	0.0370 (0.0305) (0.0340)	0.0658 (0.0298)*** (0.0310)***	0.0175 (0.0286) (0.0293)	0.0359 (0.0275) (0.0270)***	0.0386 (0.0278) (0.0278)	0.0697 (0.0318)** (0.0342)**	0.0217 (0.0257) (0.0249)	0.0189 (0.0272) (0.0266)	0.0496 (0.0276)* (0.0290)*	0.0230 (0.0260) (0.0259)
EGE1		0.0847 (0.0222)*** (0.0267)***	0.0879 (0.0223)*** (0.0268)***	0.0901 (0.0213)*** (0.0244)***	0.0519 (0.0202)** (0.0205)**	0.0600 (0.0193)*** (0.0182)***	0.0591 (0.0194)*** (0.0181)***	0.0802 (0.0255)*** (0.0282)***	0.0422 (0.0180)** (0.0170)**	0.0446 (0.0192)** (0.0173)**	0.0684 (0.0194)*** (0.0208)***	0.0477 (0.0182)*** (0.0170)***
AGE			-0.0042 (0.0022)* (0.0025)*	-0.0056 (0.0021)*** (0.0027)***	-0.0078 (0.0020)*** (0.0021)***	-0.0044 (0.0020)** (0.0020)***	-0.0069 (0.0020)*** (0.0022)***	-0.0061 (0.0026)** (0.0025)**	-0.0057 (0.0018)*** (0.0019)***	-0.0061 (0.0019)*** (0.0020)***	-0.0058 (0.0020)*** (0.0020)***	-0.0061 (0.0019)*** (0.0020)***
LFSTOCK				-0.6963 (0.0788)*** (0.0895)***								
ECACRA					-0.0131 (0.0010)*** (0.0011)***							
UNEM						0.3933 (0.1301)*** (0.1402)***		0.5955 (0.2030)*** (0.2215)***	0.4711 (0.1215)*** (0.1327)***	0.5059 (0.1272)*** (0.1374)***	0.4550 (0.1300)*** (0.1436)***	0.5122 (0.1248)*** (0.1374)***
INACTIVE							0.1725 (0.0882)* (0.0894)*					
ECACRF						-0.0111 (0.0008)*** (0.0008)***	-0.0110 (0.0008)*** (0.0009)***	-0.0083 (0.0011)*** (0.0012)***	-0.0073 (0.0008)*** (0.0009)***	-0.0073 (0.0009)*** (0.0009)***	-0.0089 (0.0008)*** (0.0010)***	-0.0072 (0.0009)*** (0.0009)***
URBANDPAV (fixed)								-0.1538 (0.0467)*** (0.0446)***				
LAT (fixed)									-0.0120 (0.0013)*** (0.0012)***			
DWSLIB										0.0621 (0.0284)** (0.0241)**		
DWSCORP										0.0594 (0.0291)** (0.0249)**		
DWSRES										0.2259 (0.0357)*** (0.0301)***		
DRLCATH											0.0955 (0.0221)*** (0.0248)***	
DRLORTH											0.2243 (0.0411)*** (0.0373)***	
DRLANGL											0.0262 (0.0219) (0.0248)	
DFNORD												-0.0599 (0.0265)** (0.0222)***
DFSC												0.1680 (0.0200)*** (0.0193)***
OBS.	604	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.12: REs: Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IMN	-0.0036 (0.0011)*** *(0.0013)****	-0.0022 (0.0011)** *(0.0014)*	-0.0016 (0.0011) *(0.0015)*	0.0012 (0.0012) *(0.0014)*	-0.0003 (0.0013) *(0.0015)*	0.0015 (0.0014) *(0.0015)*	0.0013 (0.0014) *(0.0015)*	0.0012 (0.0015) *(0.0015)*	0.0040 (0.0014)*** *(0.0014)****	0.0037 (0.0014)*** *(0.0014)***	0.0025 (0.0014)* *(0.0014)**	0.0038 (0.0014)*** *(0.0014)****
AMN		-0.0194 (0.0032)*** *(0.0034)****	-0.0203 (0.0032)*** *(0.0035)****	-0.0187 (0.0029)*** *(0.0032)****	-0.0144 (0.0028)*** *(0.0034)****	-0.0132 (0.0027)*** *(0.0032)****	-0.0121 (0.0027)*** *(0.0031)****	-0.0064 (0.0065) *(0.0076)*	-0.0090 (0.0025)*** *(0.0029)****	-0.0095 (0.0031)*** *(0.0035)****	-0.0114 (0.0031)*** *(0.0034)****	-0.0087 (0.0027)*** *(0.0032)****
AGE1		2.4000 (0.3036)*** *(0.4849)****	2.5222 (0.3046)*** *(0.4800)****	2.4649 (0.2841)*** *(0.4363)****	1.7434 (0.2884)*** *(0.4101)****	1.5539 (0.2826)*** *(0.3535)****	1.6132 (0.2828)*** *(0.3668)****	1.3460 (0.3308)*** *(0.3592)****	0.7979 (0.2819)*** *(0.2750)****	0.6693 (0.3226)** *(0.3221)***	1.3862 (0.2835)*** *(0.3296)****	0.6576 (0.3172)** *(0.3142)***
AGE			-0.0053 (0.0022)** *(0.0024)***	-0.0065 (0.0021)*** *(0.0025)****	-0.0081 (0.0021)*** *(0.0020)****	-0.0051 (0.0021)** *(0.0020)***	-0.0078 (0.0021)*** *(0.0021)****	-0.0066 (0.0026)** *(0.0025)****	-0.0067 (0.0019)*** *(0.0019)****	-0.0061 (0.0020)*** *(0.0020)****	-0.0063 (0.0021)*** *(0.0020)****	-0.0059 (0.0020)*** *(0.0020)****
LFSTOCK				-0.5853 (0.0766)*** *(0.0832)****								
ECACRA					-0.0117 (0.0012)*** *(0.0012)****							
UNEM						0.3891 (0.1350)*** *(0.1440)****		0.6187 (0.2001)*** *(0.2097)****	0.4167 (0.1286)*** *(0.1368)****	0.4798 (0.1353)*** *(0.1421)****	0.4179 (0.1344)*** *(0.1448)****	0.5019 (0.1334)*** *(0.1421)****
INACTIVE							0.1950 (0.0896)** *(0.0879)***					
ECACRF						-0.0096 (0.0009)*** *(0.0010)****	-0.0098 (0.0009)*** *(0.0010)****	-0.0073 (0.0012)*** *(0.0012)****	-0.0076 (0.0009)*** *(0.0009)****	-0.0074 (0.0010)*** *(0.0010)****	-0.0084 (0.0010)*** *(0.0010)****	-0.0074 (0.0010)*** *(0.0010)****
URBANDPAV (fixed)								-0.0963 (0.0468)** *(0.0439)***				
LAT (fixed)									-0.0114 (0.0015)*** *(0.0015)****			
DWSLIB										0.0646 (0.0668) *(0.0255)***		
DWSCORP										0.0757 (0.0662) *(0.0234)****		
DWSRES										0.1983 (0.0723)*** *(0.0372)****		
DRLCATH											0.0640 (0.0275)** *(0.0306)***	
DRLORTH											0.1728 (0.0466)*** *(0.0440)****	
DRLANGL											0.0150 (0.0310) *(0.0342)*	
DFNORD												-0.0714 (0.0653) *(0.0219)****
DFSC												0.1318 (0.0242)*** *(0.0224)****
OBS.	604	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.13: REs: Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NMN	-0.0009 (0.0008) *(0.0010)*	0.0011 (0.0010) *(0.0012)*	0.0011 (0.0010) *(0.0012)*	0.0008 (0.0010) *(0.0011)*	0.0002 (0.0013) *(0.0013)*	0.0016 (0.0010) *(0.0011)*	0.0019 (0.0010)* *(0.0011)**	0.0015 (0.0010) *(0.0011)*	0.0019 (0.0010)* *(0.0011)**
EMN		0.0564 (0.0248)** *(0.0249)***	0.0556 (0.0249)** *(0.0251)***	0.0762 (0.0251)*** *(0.0251)****	0.0783 (0.0305)** *(0.0279)****	0.0704 (0.0245)*** *(0.0249)****	0.0523 (0.0260)** *(0.0259)***	0.0705 (0.0259)*** *(0.0264)****	0.0636 (0.0245)*** *(0.0251)***
EGE1		0.0963 (0.0178)*** *(0.0168)****	0.0952 (0.0179)*** *(0.0170)****	0.0762 (0.0177)*** *(0.0158)****	0.0828 (0.0239)*** *(0.0194)****	0.0657 (0.0172)*** *(0.0163)****	0.0573 (0.0183)*** *(0.0158)****	0.0735 (0.0181)*** *(0.0168)****	0.0654 (0.0171)*** *(0.0155)****
AGE			0.0010 (0.0018) *(0.0015)*	-0.0002 (0.0018) *(0.0015)*	0.0003 (0.0024) *(0.0020)*	-0.0007 (0.0017) *(0.0015)*	-0.0003 (0.0017) *(0.0016)*	-0.0012 (0.0017) *(0.0015)*	-0.0003 (0.0017) *(0.0015)*
ECACRF				-0.0037 (0.0006)*** *(0.0006)****	-0.0019 (0.0009)** *(0.0009)***	-0.0014 (0.0007)** *(0.0007)***	-0.0011 (0.0008) *(0.0008)*	-0.0025 (0.0007)*** *(0.0007)****	-0.0006 (0.0008) *(0.0007)*
URBANDP AV (fixed)					-0.0308 (0.0377) *(0.0334)*				
LAT (fixed)						-0.0059 (0.0012)*** *(0.0011)****			
DWSLIB							0.0888 (0.0223)*** *(0.0181)****		
DWSCORP							0.0721 (0.0234)*** *(0.0174)****		
DWSRES							0.1482 (0.0298)*** *(0.0226)****		
DRLCATH								0.0474 (0.0171)*** *(0.0194)***	
DRLORTH								0.1645 (0.0315)*** *(0.0331)****	
DRLANGL								0.0412 (0.0164)** *(0.0193)***	
DFNORD									-0.0840 (0.0209)*** *(0.0158)****
DFSC									0.0773 (0.0166)*** *(0.0149)****
OBS.	604	596	596	513	299	513	513	513	513

Appendix A6.14: REs: Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NMN	-0.0009 (0.0008) *(0.0010)*	0.0004 (0.0008) *(0.0011)*	0.0002 (0.0008) *(0.0012)*	0.0003 (0.0010) *(0.0012)*	0.0000 (0.0012) *(0.0012)*	0.0010 (0.0010) *(0.0012)*	0.0009 (0.0010) *(0.0012)*	0.0008 (0.0010) *(0.0012)*	0.0010 (0.0010) *(0.0012)*
AMN		-0.0123 (0.0021)*** *(0.0023)******	-0.0120 (0.0021)*** *(0.0023)****	-0.0083 (0.0023)*** *(0.0026)****	-0.0109 (0.0057)* *(0.0069)*	-0.0063 (0.0024)*** *(0.0026)***	-0.0048 (0.0028)* *(0.0031)*	-0.0056 (0.0028)** *(0.0029)**	-0.0058 (0.0025)** *(0.0027)***
AGE1		1.2382 (0.2257)*** *(0.2514)****	1.1868 (0.2305)*** *(0.2527)****	0.7575 (0.2627)*** *(0.2627)****	0.8396 (0.3160)*** *(0.3206)****	0.4340 (0.2761) *(0.2474)**	0.3431 (0.3157) *(0.3090)*	0.7939 (0.2633)*** *(0.2720)****	0.2665 (0.3085) *(0.2906)*
AGE			0.0020 (0.0019) *(0.0016)*	0.0006 (0.0019) *(0.0016)*	-0.0002 (0.0024) *(0.0021)*	0.0002 (0.0018) *(0.0016)*	0.0006 (0.0019) *(0.0016)*	-0.0005 (0.0019) *(0.0016)*	0.0004 (0.0018) *(0.0016)*
ECACRF				-0.0018 (0.0008)** *(0.0008)***	-0.0008 (0.0009) *(0.0009)*	-0.0007 (0.0008) *(0.0008)*	-0.0011 (0.0009) *(0.0008)*	-0.0017 (0.0008)* *(0.0008)***	-0.0005 (0.0008) *(0.0008)*
URBANDP AV (fixed)					0.0028 (0.0372) *(0.0343)*				
LAT (fixed)						-0.0044 (0.0014)*** *(0.0013)****			
DWSLIB							0.0756 (0.0541) *(0.0264)****		
DWSCORP							0.1145 (0.0536) *(0.0242)***		
DWSRES							0.0581 (0.0599)* *(0.0359)****		
DRLCATH								0.0262 (0.0215) *(0.0244)*	
DRLORTH								0.1320 (0.0364)*** *(0.0386)****	
DRLANGL								0.0333 (0.0249) *(0.0280)*	
DFNORD									-0.0677 (0.0517) *(0.0231)****
DFSC									0.0596 (0.0213)*** *(0.0196)****
OBS.	604	534	534	455	299	455	455	455	455

Appendix A6.15: REs: Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EMN	-1.1075 (0.0242)*** _(0.0262)_***	-1.1009 (0.0322)*** _(0.0384)_***	-1.0979 (0.0322)*** _(0.0382)_***	-1.1034 (0.0332)*** _(0.0386)_***	-1.1353 (0.0363)*** _(0.0445)_***	-1.1379 (0.0368)*** _(0.0451)_***	-1.1373 (0.0370)*** _(0.0446)_***	-1.0086 (0.0400)*** _(0.0324)_***	-1.1366 (0.0368)*** _(0.0450)_***	-1.1580 (0.0360)*** _(0.0442)_***	-1.1515 (0.0366)*** _(0.0422)_***	-1.1397 (0.0369)*** _(0.0450)_***
IMN		0.0013 (0.0026) _(0.0023)_	0.0003 (0.0026) _(0.0024)_	-0.0007 (0.0027) _(0.0026)_	0.0003 (0.0033) _(0.0029)_	-0.0014 (0.0034) _(0.0030)_	-0.0002 (0.0034) _(0.0029)_	-0.0064 (0.0038)* _(0.0025)_**	-0.0002 (0.0035) _(0.0030)_	0.0007 (0.0035) _(0.0028)_	-0.0045 (0.0033) _(0.0032)_	-0.0011 (0.0036) _(0.0029)_
IGE1		0.2844 (0.0745)*** _(0.0795)_***	0.2935 (0.0746)*** _(0.0800)_***	0.3125 (0.0776)*** _(0.0822)_***	0.2372 (0.0963)** _(0.0859)_***	0.2966 (0.1002)*** _(0.0872)_***	0.2685 (0.0995)*** _(0.0861)_***	0.3963 (0.1281)*** _(0.1320)_***	0.2326 (0.1069)** _(0.0905)_**	0.2413 (0.1026)** _(0.0853)_***	0.3719 (0.0997)*** _(0.0953)_***	0.2595 (0.1066)** _(0.0927)_***
AGE			0.0068 (0.0040)* _(0.0039)_*	0.0077 (0.0040)* _(0.0041)_*	0.0062 (0.0045) _(0.0045)_	0.0057 (0.0045) _(0.0045)_	0.0065 (0.0046) _(0.0051)_	0.0091 (0.0057) _(0.0051)_*	0.0047 (0.0046) _(0.0044)_	0.0077 (0.0044)* _(0.0042)_*	0.0113 (0.0045)** _(0.0045)_**	0.0060 (0.0046) _(0.0047)_
LFSTOCK				0.1386 (0.1573) _(0.1396)_								
ECACRA					-0.0002 (0.0026) _(0.0021)_							
UNEM						-0.2987 (0.2981) _(0.2370)_		0.1143 (0.4533) _(0.4163)_	-0.2283 (0.3008) _(0.2266)_	0.1034 (0.2989) _(0.2250)_	-0.0431 (0.2986) _(0.2465)_	-0.1833 (0.3064) _(0.2377)_
INACTIVE							-0.0255 (0.1968) _(0.1899)_					
ECACRF						0.0016 (0.0021) _(0.0017)_	0.0010 (0.0022) _(0.0018)_	-0.0008 (0.0028) _(0.0031)_	0.0030 (0.0022) _(0.0020)_	0.0027 (0.0023) _(0.0021)_	0.0020 (0.0021) _(0.0018)_	0.0041 (0.0023)* _(0.0021)_*
URBANDPAV (fixed)								0.3561 (0.1200)*** _(0.0913)_***				
LAT (fixed)									-0.0066 (0.0038)* _(0.0038)_*			
DWSLIB										0.2691 (0.0640)*** _(0.0382)_***		
DWSCORP										-0.0126 (0.0667) _(0.0501)_		
DWSRES										0.1650 (0.0848)** _(0.0578)_***		
DRLCATH											0.0490 (0.0487) _(0.0383)_	
DRLORTH											-0.0230 (0.0914) _(0.0777)_	
DRLANGL											0.2812 (0.0456)*** _(0.0267)_***	
DFNORD												-0.1386 (0.0700)** _(0.0432)_***
DFSC												0.0469 (0.0547) _(0.0446)_
OBS.	596	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.16: REs: Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EMN	-1.1075 (0.0242)*** *(0.0262)****	-1.0950 (0.0310)*** *(0.0359)****	-1.0943 (0.0310)*** *(0.0358)****	-1.0986 (0.0327)*** *(0.0365)****	-1.1265 (0.0353)*** *(0.0408)****	-1.1322 (0.0357)*** *(0.0422)****	-1.1296 (0.0364)*** *(0.0422)****	-1.0147 (0.0394)*** *(0.0324)****	-1.1267 (0.0357)*** *(0.0416)****	-1.1492 (0.0350)*** *(0.0414)****	-1.1503 (0.0357)*** *(0.0391)****	-1.1314 (0.0358)*** *(0.0422)****
NMN		-0.0012 (0.0020) *(0.0016)*	-0.0018 (0.0020) *(0.0017)*	-0.0025 (0.0021) *(0.0018)*	-0.0028 (0.0025) *(0.0021)*	-0.0034 (0.0025) *(0.0021)*	-0.0029 (0.0025) *(0.0021)*	-0.0047 (0.0029) *(0.0019)***	-0.0026 (0.0025) *(0.0021)*	-0.0014 (0.0025) *(0.0019)*	-0.0053 (0.0025)** *(0.0022)***	-0.0030 (0.0026) *(0.0020)*
NGE1		0.3348 (0.0840)*** *(0.0746)****	0.3321 (0.0839)*** *(0.0742)****	0.3604 (0.0858)*** *(0.0790)****	0.3424 (0.1047)*** *(0.0952)****	0.3679 (0.1053)*** *(0.0986)****	0.3526 (0.1051)*** *(0.0986)****	0.3955 (0.1289)*** *(0.1261)****	0.3282 (0.1068)*** *(0.0995)****	0.2838 (0.1048)*** *(0.0925)****	0.3710 (0.1054)*** *(0.1028)****	0.3291 (0.1074)*** *(0.0984)****
AGE			0.0063 (0.0040) *(0.0038)*	0.0070 (0.0040)* *(0.0039)**	0.0058 (0.0043) *(0.0044)*	0.0048 (0.0045) *(0.0043)*	0.0059 (0.0045) *(0.0048)*	0.0066 (0.0057) *(0.0048)*	0.0041 (0.0045) *(0.0043)*	0.0069 (0.0044) *(0.0041)**	0.0097 (0.0044)** *(0.0043)***	0.0052 (0.0045) *(0.0045)*
LFSTOCK				0.0740 (0.1492) *(0.1345)*								
ECACRA					-0.0008 (0.0022) *(0.0022)*							
UNEM						-0.2914 (0.2942) *(0.2295)*		0.2650 (0.4492) *(0.3930)*	-0.2358 (0.2946) *(0.2212)*	0.1076 (0.2938) *(0.2205)*	0.0164 (0.2952) *(0.2396)*	-0.1700 (0.3002) *(0.2283)*
INACTIVE							-0.0061 (0.1974) *(0.1849)*					
ECACRF						-0.0001 (0.0018) *(0.0018)*	0.0001 (0.0018) *(0.0019)*	-0.0031 (0.0026) *(0.0035)*	0.0021 (0.0021) *(0.0020)*	0.0014 (0.0021) *(0.0021)*	-0.0005 (0.0018) *(0.0020)*	0.0026 (0.0022) *(0.0022)*
URBANDPAV (fixed)								0.2937 (0.1163)** *(0.0853)****				
LAT (fixed)									-0.0072 (0.0035)** *(0.0037)**			
DWSLIB										0.2557 (0.0643)*** *(0.0351)****		
DWSCORP										-0.0135 (0.0666) *(0.0477)*		
DWSRES										0.1674 (0.0823)** *(0.0505)****		
DRLCATH											0.0651 (0.0473) *(0.0345)**	
DRLORTH											-0.0151 (0.0888) *(0.0668)*	
DRLANGL											0.2708 (0.0452)*** *(0.0262)****	
DFNORD												-0.1298 (0.0698)* *(0.0406)****
DFSC												0.0554 (0.0512) *(0.0427)*
OBS.	596	596	596	596	513	513	513	299	513	513	513	513

Appendix A6.17: REs: Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AMN	0.0036 (0.0004)*** (0.0006)***	0.0039 (0.0004)*** (0.0004)***	0.0040 (0.0004)*** (0.0004)***	0.0040 (0.0004)*** (0.0004)***	0.0040 (0.0004)*** (0.0004)***	0.0041 (0.0004)*** (0.0004)***	0.0040 (0.0004)*** (0.0004)***	0.0061 (0.0011)*** (0.0015)***	0.0043 (0.0004)*** (0.0004)***	0.0047 (0.0004)*** (0.0004)***	0.0038 (0.0005)*** (0.0005)***	0.0045 (0.0003)*** (0.0004)***
IMN		-0.0003 (0.0001)** (0.0002)*	-0.0005 (0.0002)*** (0.0002)***	-0.0005 (0.0002)*** (0.0002)***	-0.0006 (0.0002)*** (0.0003)**	-0.0005 (0.0002)** (0.0003)**	-0.0006 (0.0002)*** (0.0003)**	-0.0003 (0.0003) (0.0003)	-0.0001 (0.0002) (0.0002)	0.0001 (0.0002) (0.0002)	-0.0005 (0.0002)** (0.0002)**	0.0001 (0.0002) (0.0002)
IGE1		0.0447 (0.0056)*** (0.0052)***	0.0466 (0.0055)*** (0.0053)***	0.0469 (0.0058)*** (0.0056)***	0.0434 (0.0071)*** (0.0067)***	0.0404 (0.0074)*** (0.0067)***	0.0417 (0.0073)*** (0.0066)***	0.0391 (0.0098)*** (0.0092)***	0.0240 (0.0076)*** (0.0068)***	0.0098 (0.0068) (0.0061)	0.0366 (0.0075)*** (0.0064)***	0.0124 (0.0070)* (0.0062)**
AGE			0.0012 (0.0003)*** (0.0004)***	0.0012 (0.0003)*** (0.0004)***	0.0011 (0.0003)*** (0.0004)***	0.0012 (0.0003)*** (0.0004)***	0.0012 (0.0003)*** (0.0004)***	0.0011 (0.0004)** (0.0005)**	0.0008 (0.0003)** (0.0004)**	0.0007 (0.0003)** (0.0003)**	0.0011 (0.0003)*** (0.0004)***	0.0007 (0.0003)** (0.0003)**
LFSTOCK				-0.0029 (0.0114) (0.0100)								
ECACRA					-0.0003 (0.0002)* (0.0002)*							
UNEM						0.0105 (0.0220) (0.0192)		-0.0147 (0.0348) (0.0326)	0.0219 (0.0212) (0.0173)	0.0421 (0.0198)** (0.0167)**	0.0077 (0.0221) (0.0184)	0.0429 (0.0200)** (0.0161)***
INACTIVE							-0.0147 (0.0144) (0.0134)					
ECACRF						-0.0004 (0.0002)** (0.0002)**	-0.0004 (0.0002)** (0.0002)***	-0.0004 (0.0002)** (0.0002)**	-0.0001 (0.0002) (0.0001)	0.0001 (0.0001) (0.0001)	-0.0002 (0.0002) (0.0002)	0.0001 (0.0002) (0.0001)
URBANDPAV (fixed)								-0.0227 (0.0083)*** (0.0093)**				
LAT (fixed)									-0.0018 (0.0003)*** (0.0003)***			
DWSLIB										0.0183 (0.0083)** (0.0195)		
DWSCORP										0.0171 (0.0082)** (0.0194)		
DWSRES										0.0574 (0.0090)*** (0.0198)***		
DRLCATH											0.0091 (0.0046)** (0.0042)**	
DRLORTH											0.0018 (0.0079) (0.0086)	
DRLANGL											-0.0036 (0.0051) (0.0050)	
DFNORD												-0.0167 (0.0090)* (0.0214)
DFSC												0.0375 (0.0031)*** (0.0030)***
OBS.	534	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.18: REs: Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AMN	0.0036 (0.0004)*** (0.0006)***	0.0034 (0.0004)*** (0.0005)***	0.0035 (0.0004)*** (0.0005)***	0.0036 (0.0004)*** (0.0005)***	0.0037 (0.0004)*** (0.0005)***	0.0038 (0.0004)*** (0.0005)***	0.0038 (0.0004)*** (0.0005)***	0.0061 (0.0011)*** (0.0015)***	0.0042 (0.0004)*** (0.0004)***	0.0046 (0.0004)*** (0.0004)***	0.0035 (0.0005)*** (0.0005)***	0.0045 (0.0003)*** (0.0004)***
NMN		-0.0003 (0.0001)** (0.0002)*	-0.0004 (0.0001)*** (0.0001)***	-0.0003 (0.0001)** (0.0001)**	-0.0005 (0.0002)*** (0.0002)**	-0.0004 (0.0002)** (0.0002)*	-0.0004 (0.0002)** (0.0002)**	-0.0003 (0.0002) (0.0002)	-0.0001 (0.0002) (0.0002)	0.0001 (0.0002) (0.0002)	-0.0004 (0.0002)** (0.0002)**	0.0001 (0.0002) (0.0002)
NGE1		0.0263 (0.0064)*** (0.0061)***	0.0257 (0.0064)*** (0.0062)***	0.0237 (0.0065)*** (0.0062)***	0.0225 (0.0080)*** (0.0072)***	0.0212 (0.0080)*** (0.0068)***	0.0221 (0.0080)*** (0.0068)***	0.0250 (0.0101)** (0.0083)***	0.0131 (0.0076)* (0.0060)**	0.0071 (0.0071) (0.0062)	0.0219 (0.0080)*** (0.0064)***	0.0074 (0.0072) (0.0061)
AGE			0.0009 (0.0003)*** (0.0004)**	0.0009 (0.0003)*** (0.0004)**	0.0007 (0.0003)** (0.0004)*	0.0010 (0.0003)*** (0.0004)**	0.0009 (0.0003)*** (0.0004)**	0.0009 (0.0004)* (0.0005)	0.0007 (0.0003)** (0.0004)*	0.0007 (0.0003)** (0.0003)*	0.0009 (0.0003)*** (0.0004)**	0.0007 (0.0003)** (0.0003)*
LFSTOCK				-0.0274 (0.0110)** (0.0102)***								
ECACRA					-0.0009 (0.0002)*** (0.0002)***							
UNEM						0.0253 (0.0223) (0.0195)		0.0032 (0.0348) (0.0323)	0.0291 (0.0210) (0.0171)*	0.0446 (0.0195)** (0.0163)***	0.0185 (0.0223) (0.0188)	0.0466 (0.0196)** (0.0158)***
INACTIVE							-0.0065 (0.0148) (0.0139)					
ECACRF						-0.0008 (0.0001)*** (0.0001)***	-0.0009 (0.0001)*** (0.0001)***	-0.0008 (0.0002)*** (0.0002)***	-0.0003 (0.0002)** (0.0001)**	0.0001 (0.0001) (0.0001)	-0.0005 (0.0002)*** (0.0002)***	0.0001 (0.0001) (0.0001)
URBANDP AV (fixed)								-0.0274 (0.0082)*** (0.0089)***				
LAT (fixed)									-0.0020 (0.0003)*** (0.0003)***			
DWSLIB										0.0182 (0.0084)** (0.0198)		
DWSCORP										0.0172 (0.0083)** (0.0197)		
DWSRES										0.0583 (0.0089)*** (0.0199)***		
DRLCATH											0.0107 (0.0045)** (0.0042)**	
DRLORTH											0.0042 (0.0077) (0.0081)	
DRLANGL											-0.0047 (0.0051) (0.0051)	
DFNORD												-0.0169 (0.0089)* (0.0214)
DFSC												0.0386 (0.0029)*** (0.0026)***
OBS.	534	534	534	534	455	455	455	299	455	455	455	455

Appendix A6.19: Short Run GMM: Dependent Variable is IGE1 and Independent Variables are EMN and EGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(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)
$LFSTOCK_{it}$ $LFSTOCK_{i,t}$										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)
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$												

$INACTIVE_{i,t}$												
$ECACRF_{it}$ $ECACRF_{i,t-1}$												
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)*

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(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} $IMN_{i,t-1}$	0.0163 (0.0040)*** *(0.0047)**** -0.0106 (0.0045)** *(0.0056)**	0.0054 (0.0062) *(0.0074)* 0.0016 (0.0062) *(0.0081)*	0.0075 (0.0077) *(0.0096)* -0.0037 (0.0076) *(0.0108)*	0.0168 (0.0043)*** *(0.0049)**** -0.0130 (0.0048)*** *(0.0060)***	0.0127 (0.0056)** *(0.0060)*** -0.0042 (0.0054) *(0.0059)*	0.0138 (0.0071)* *(0.0076)** -0.0083 (0.0070) *(0.0080)*	0.0157 (0.0042)*** *(0.0048)**** -0.0128 (0.0047)*** *(0.0055)***	0.0095 (0.0058) *(0.0063)* -0.0021 (0.0055) *(0.0062)*	0.0109 (0.0071) *(0.0081)* -0.0050 (0.0069) *(0.0076)*			
EMN_{it} $EMN_{i,t-1}$	0.0780 (0.0520) *(0.0563)* -0.1182 (0.0473)** *(0.0534)***	0.0277 (0.0751) *(0.0979)* -0.0978 (0.0513)* *(0.0503)**	0.0391 (0.0899) *(0.1158)* -0.1689 (0.0679)** *(0.0810)***	0.0851 (0.0548) *(0.0541)* -0.1214 (0.0504)** *(0.0560)***	0.0866 (0.0654) *(0.0697)* -0.1057 (0.0486)** *(0.0474)***	0.1129 (0.0841) *(0.0960)* -0.1273 (0.0628)** *(0.0676)**	0.0865 (0.0539) *(0.0533)* -0.1267 (0.0498)** *(0.0588)***	0.0312 (0.0669) *(0.0618)* -0.0900 (0.0506)* *(0.0508)**	-0.0036 (0.0846) *(0.0849)* -0.1188 (0.0635)* *(0.0739)*			
$EGE1_{it}$ $EGE1_{i,t-1}$	0.0456 (0.0318) *(0.0269)** -0.0655 (0.0317)** *(0.0263)***	0.0765 (0.0448)* *(0.0527)* -0.0659 (0.0351)* *(0.0282)***	0.0504 (0.0618) *(0.0590)* -0.1297 (0.0537)** *(0.0520)***	0.0511 (0.0337) *(0.0287)** -0.0664 (0.0336)** *(0.0282)***	0.0702 (0.0404)* *(0.0406)** -0.0429 (0.0319) *(0.0205)***	0.0439 (0.0559) *(0.0526)* -0.0587 (0.0464) *(0.0388)*	0.0525 (0.0331) *(0.0272)** -0.0715 (0.0332)** *(0.0300)***	0.0524 (0.0424) *(0.0369)* -0.0511 (0.0342) *(0.0252)***	0.0016 (0.0578) *(0.0601)* -0.0592 (0.0470) *(0.0480)*			
AGE_{it} $AGE_{i,t-1}$	0.0080 (0.0049)* *(0.0057)* -0.0011 (0.0030)	0.0013 (0.0050) *(0.0061)* -0.0070 (0.0027)**	0.0027 (0.0055) *(0.0070)* -0.0033 (0.0031)	0.0083 (0.0051) *(0.0055)* -0.0021 (0.0032)	0.0050 (0.0046) *(0.0053)* -0.0059 (0.0026)**	0.0088 (0.0054) *(0.0068)* -0.0005 (0.0031)	0.0108 (0.0053)** *(0.0056)** -0.0022 (0.0032)	0.0080 (0.0055) *(0.0062)* -0.0071 (0.0029)**	0.0113 (0.0063)* *(0.0075)* -0.0030 (0.0032)			

	_(0.0036)_	_(0.0032)_**	_(0.0035)_	_(0.0036)_	_(0.0031)_*	_(0.0035)_	_(0.0037)_	_(0.0035)_**	_(0.0035)_			
$LFSTOCK_{it}$ $LFSTOCK_{i,t}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	-0.0078 (0.0022)*** _(0.0021)_*** -0.0046 (0.0023)** _(0.0021)_**	-0.0051 (0.0035) _(0.0036)_ -0.0067 (0.0032)** _(0.0032)_**	-0.0072 (0.0042)* _(0.0039)_* -0.0082 (0.0046)* _(0.0050)_									
$UNEM_{it}$ $UNEM_{i,t-1}$				-0.0865 (0.2213) _(0.1836)_ -0.3702 (0.2206)* _(0.2556)_	0.1723 (0.3225) _(0.3195)_ 0.2074 (0.2431) _(0.2703)_	0.2386 (0.3890) _(0.3674)_ 0.8445 (0.3645)** _(0.2979)_***						
$INACTIVE_{it}$ $INACTIVE_{i,t}$							-0.4672 (0.1766)*** _(0.2104)_** 0.0567 (0.1394) _(0.1236)_	-0.6287 (0.3249)* _(0.3580)_* 0.2356 (0.1733) _(0.1577)_	-0.8120 (0.4393)* _(0.5851)_ -0.3325 (0.3420) _(0.3591)_			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				-0.0048 (0.0020)** _(0.0020)_** -0.0056 (0.0021)*** _(0.0020)_***	-0.0043 (0.0026) _(0.0025)_* -0.0059 (0.0026)** _(0.0030)_**	-0.0066 (0.0034)** _(0.0032)_** -0.0033 (0.0040) _(0.0043)_	-0.0053 (0.0019)*** _(0.0021)_** -0.0052 (0.0020)** _(0.0019)_***	-0.0062 (0.0033)* _(0.0029)_** -0.0036 (0.0028) _(0.0030)_	-0.0132 (0.0047)*** _(0.0051)_** -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)_			

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator. 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.

Appendix A6.20: Short Run GMM: Dependent Variable is IGE1 and Independent Variables are AMN and AGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(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)_***	0.6006 (0.1289)*** _(0.1606)_***	0.2682 (0.1242)** _(0.1669)_	0.2967 (0.1709)* _(0.1754)_*	0.6086 (0.1292)*** _(0.1702)_***	0.2600 (0.1222)** _(0.1690)_	0.2828 (0.1689)* _(0.1777)_	0.6433 (0.1426)*** _(0.1838)_***	0.2802 (0.1313)** _(0.1975)_	0.2909 (0.1798) _(0.2479)_
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)_	0.0124 (0.0025)*** _(0.0026)_*** -0.0025 (0.0033) _(0.0034)_	0.0066 (0.0029)** _(0.0032)_** 0.0025 (0.0037) _(0.0042)_	0.0094 (0.0039)** _(0.0050)_* 0.0028 (0.0042) _(0.0047)_	0.0129 (0.0025)*** _(0.0027)_*** -0.0033 (0.0033) _(0.0036)_	0.0073 (0.0029)** _(0.0030)_** 0.0024 (0.0037) _(0.0043)_	0.0097 (0.0039)** _(0.0048)_** 0.0032 (0.0041) _(0.0048)_	0.0128 (0.0026)*** _(0.0027)_*** -0.0040 (0.0037) _(0.0042)_	0.0067 (0.0031)** _(0.0032)_** 0.0023 (0.0042) _(0.0051)_	0.0109 (0.0043)** _(0.0050)_** 0.0006 (0.0048) _(0.0064)_
AMN_{it} $AMN_{i,t-1}$				0.0128 (0.0066)* _(0.0053)_** -0.0018 (0.0084) _(0.0060)_	0.0179 (0.0097)* _(0.0117)_ 0.0009 (0.0126) _(0.0137)_	0.0099 (0.0110) _(0.0115)_ 0.0160 (0.0146) _(0.0153)_	0.0133 (0.0067)** _(0.0053)_** -0.0010 (0.0084) _(0.0057)_	0.0173 (0.0096)* _(0.0114)_ 0.0020 (0.0125) _(0.0142)_	0.0114 (0.0110) _(0.0113)_ 0.0171 (0.0145) _(0.0158)_	0.0133 (0.0068)* _(0.0054)_** -0.0016 (0.0086)*** _(0.0058)_	0.0120 (0.0100) _(0.0109)_ -0.0007 (0.0127) _(0.0144)_	0.0058 (0.0125) _(0.0121)_ 0.0186 (0.0151) _(0.0171)_
$AGE1_{it}$ $AGE1_{i,t-1}$				0.1297 (0.4545) _(0.4278)_ 1.3248 (0.6237)** _(0.5281)_**	2.1196 (0.9680)** _(1.2177)_* 2.7477 (0.9932)*** _(1.0891)_**	2.2061 (1.2600)* _(1.4654)_ 1.6044 (1.5886) _(1.5294)_	0.0732 (0.4576) _(0.4010)_ 1.3626 (0.6237)** _(0.5238)_***	1.9597 (0.9747)** _(1.1677)_* 2.8579 (0.9689)*** _(1.0931)_***	2.1319 (1.2785)* _(1.4602)_ 1.5218 (1.5780) _(1.4669)_	0.0633 (0.4655) _(0.4066)_ 1.3366 (0.6354)** _(0.5247)_**	2.9557 (0.9795)*** _(1.4496)_** 2.4976 (1.0276)** _(1.1217)_**	3.2514 (1.2482)*** _(1.8339)_* 1.8898 (1.5999) _(1.5306)_
AGE_{it} $AGE_{i,t-1}$							0.0095 (0.0046)** _(0.0049)_* -0.0009 (0.0030) _(0.0030)_	0.0058 (0.0043) _(0.0050)_ -0.0010 (0.0027) _(0.0026)_	0.0061 (0.0044) _(0.0048)_ -0.0004 (0.0027) _(0.0026)_	0.0099 (0.0048)** _(0.0053)_* -0.0011 (0.0031) _(0.0031)_	0.4100 (0.2582) _(0.3006)_ -0.2424 (0.1920) _(0.2153)_	0.7367 (0.3069)** _(0.4008)_* 0.1065 (0.3435) _(0.3651)_
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										0.0847 (0.1393) _(0.1655)_ 0.0177 (0.1187) _(0.1009)_	0.0064 (0.0046) _(0.0058)_ -0.0020 (0.0029) _(0.0029)_	0.0079 (0.0050) _(0.0060)_ -0.0021 (0.0032) _(0.0031)_
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$												

$INACTIVE_{i,t-1}$												
$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	400			348			348			348		
SARGAN TEST (p-value)	12.26 (0.1989)	26.20 (0.0709)	18.09 (0.1541)	14.06 (0.1200)	49.74 (0.0309)	33.77 (0.0383)	13.14 (0.1562)	50.84 (0.0244)	35.08 (0.0277)	12.37 (0.1935)	49.17 (0.1784)	25.33 (0.4440)
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)*	-4.33 (0.0000) *-2.96* *(0.0031)*	-2.07 (0.0388) *-1.62* *(0.1054)*	-1.70 (0.0882) *-1.83* *(0.0676)*	-4.38 (0.0000) *-2.86* *(0.0043)*	-2.03 (0.0427) *-1.57* *(0.1172)*	-1.67 (0.0941) *-1.78* *(0.0743)*	-4.40 (0.0000) *-2.95* *(0.0032)*	-2.18 (0.0289) *-1.60* *(0.1105)*	-0.94 (0.3487) *-0.80* *(0.4264)*
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)*	-1.35 (0.1774) *-0.77* *(0.4387)*	-1.42 (0.1561) *-0.85* *(0.3977)*	-1.13 (0.2598) *-0.74* *(0.4583)*	-1.21 (0.2252) *-0.69* *(0.4904)*	-1.40 (0.1602) *-0.82* *(0.4097)*	-0.95 (0.3431) *-0.64* *(0.5222)*	-1.11 (0.2653) *-0.65* *(0.5168)*	-0.77 (0.4427) *-0.49* *(0.6216)*	-0.26 (0.7980) *-0.19* *(0.8455)*

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous			
$IGE1_{i,t-1}$	0.4541 (0.1313)*** *(0.1622)****	0.2664 (0.1133)** *(0.1265)***	0.2386 (0.1440)* *(0.1529)*	0.5480 (0.1410)*** *(0.1762)****	0.2557 (0.1036)** *(0.0972)****	0.1426 (0.1262) *(0.1458)*	0.5627 (0.1378)*** *(0.1673)****	0.3869 (0.1064)*** *(0.0996)****	0.3719 (0.1248)*** *(0.1146)****			
IMN_{it} $IMN_{i,t-1}$	0.0115 (0.0031)*** *(0.0029)**** -0.0052 (0.0035) *(0.0038)*	0.0054 (0.0034) *(0.0032)** -0.0033 (0.0036) *(0.0042)*	0.0043 (0.0038) *(0.0037)* -0.0054 (0.0044) *(0.0050)*	0.0121 (0.0033)*** *(0.0033)**** -0.0068 (0.0038)* *(0.0042)*	0.0077 (0.0035)** *(0.0037)*** -0.0041 (0.0035) *(0.0038)*	0.0064 (0.0039) *(0.0046)* -0.0020 (0.0041) *(0.0043)*	0.0104 (0.0032)*** *(0.0031)**** -0.0067 (0.0038)* *(0.0042)*	0.0061 (0.0035)* *(0.0032)** -0.0042 (0.0040) *(0.0046)*	0.0062 (0.0038) *(0.0037)** -0.0047 (0.0049) *(0.0053)*			
AMN_{it} $AMN_{i,t-1}$	0.0092 (0.0064) *(0.0048)** -0.0010 (0.0079) *(0.0055)*	0.0048 (0.0089) *(0.0097)* 0.0070 (0.0113) *(0.0128)*	-0.0087 (0.0116) *(0.0113)* 0.0171 (0.0130) *(0.0142)*	0.0097 (0.0068) *(0.0053)** -0.0032 (0.0086) *(0.0061)*	0.0094 (0.0085) *(0.0094)* -0.0004 (0.0121) *(0.0155)*	0.0032 (0.0115) *(0.0123)* 0.0138 (0.0150) *(0.0216)*	0.0083 (0.0068) *(0.0050)** -0.0025 (0.0083) *(0.0058)*	0.0032 (0.0093) *(0.0107)* -0.0011 (0.0114) *(0.0125)*	-0.0054 (0.0124) *(0.0121)* 0.0139 (0.0136) *(0.0152)*			
$AGE1_{it}$ $AGE1_{i,t-1}$	-0.0753 (0.4481) *(0.3143)* 1.2372 (0.5816)** *(0.5570)***	0.7177 (0.8543) *(1.1031)* 2.3077 (0.8055)*** *(0.7294)****	1.3473 (1.0962) *(1.3324)* 1.9888 (1.1065)* *(1.2050)**	-0.0508 (0.4734) *(0.3498)* 1.3452 (0.6129)** *(0.5518)***	0.6524 (0.7649) *(0.8520)* 2.9948 (0.7730)*** *(0.8556)****	1.4672 (0.9530) *(1.0831)* 3.4025 (1.0030)*** *(1.2075)****	-0.1134 (0.4727) *(0.3260)* 1.1975 (0.6189)* *(0.5167)***	0.2461 (0.8587) *(0.8394)* 2.2348 (0.8347)*** *(0.7560)****	0.9953 (1.0069) *(0.9492)* 1.7921 (1.0027)* *(0.9396)**			
AGE_{it} $AGE_{i,t-1}$	0.0098 (0.0050)** *(0.0062)* -0.0012 (0.0029)	0.0081 (0.0046)* *(0.0060)* -0.0022 (0.0027)	0.0062 (0.0049) *(0.0056)* -0.0017 (0.0028)	0.0097 (0.0052)* *(0.0057)** -0.0019 (0.0031)	0.0078 (0.0048) *(0.0051)* -0.0027 (0.0027)	0.0053 (0.0051) *(0.0053)* -0.0024 (0.0028)	0.0112 (0.0054)** *(0.0062)** -0.0019 (0.0031)	0.0093 (0.0054)* *(0.0057)* -0.0032 (0.0029)	0.0096 (0.0057)* *(0.0061)* -0.0031 (0.0031)			

	(0.0032)	*(0.0029)*	*(0.0030)*	*(0.0032)*	*(0.0027)*	*(0.0027)*	*(0.0035)*	*(0.0036)*	*(0.0036)*			
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	-0.0073 (0.0021)*** *(0.0018)**** -0.0041 (0.0024)* *(0.0023)**	-0.0065 (0.0033)* *(0.0035)** -0.0076 (0.0039)** *(0.0047)*	-0.0065 (0.0039)* *(0.0035)** -0.0112 (0.0048)** *(0.0052)***									
$UNEM_{it}$ $UNEM_{i,t-1}$				-0.1851 (0.2218) *(0.1782)* -0.4068 (0.2092)* *(0.2479)*	-0.1464 (0.3262) *(0.4192)* -0.2677 (0.2208) *(0.3191)*	-0.0605 (0.3947) *(0.5950)* -0.5017 (0.3643) *(0.4883)*						
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$							-0.2821 (0.1768) *(0.1998)* 0.1617 (0.1413) *(0.1203)*	-0.1607 (0.3121) *(0.2956)* 0.4753 (0.1726)*** *(0.2005)***	-0.3470 (0.3630) *(0.4030)* 0.3675 (0.3276) *(0.3413)*			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				-0.0050 (0.0019)** *(0.0019)**** -0.0048 (0.0021)** *(0.0021)***	-0.0049 (0.0032) *(0.0036)* -0.0059 (0.0033)* *(0.0038)*	-0.0024 (0.0039) *(0.0042)* -0.0087 (0.0044)** *(0.0049)**	-0.0050 (0.0020)** *(0.0019)**** -0.0045 (0.0021)** *(0.0021)***	-0.0069 (0.0034)** *(0.0035)*** -0.0065 (0.0033)** *(0.0037)**	-0.0064 (0.0046) *(0.0041)* -0.0065 (0.0044) *(0.0046)*			
OBS.	285			285			285					
SARGAN TEST (p-value)	11.12 (0.2675)	44.72 (0.3185)	25.53 (0.4328)	10.39 (0.3201)	69.59 (0.0281)	42.02 (0.0560)	8.60 (0.4746)	53.97 (0.2900)	34.56 (0.2194)			
AR(1) TEST (p-value)	-3.95 (0.0001) *-2.80* *(0.0051)*	-3.31 (0.0009) *-2.65* *(0.0081)*	-2.93 (0.0034) *-2.62* *(0.0089)*	-4.07 (0.0000) *-2.88* *(0.0039)*	-3.07 (0.0021) *-2.54* *(0.0112)*	-1.72 (0.0846) *-1.38* *(0.1683)*	-4.42 (0.0000) *-3.21* *(0.0013)*	-4.13 (0.0000) *-3.37* *(0.0008)*	-3.43 (0.0006) *-3.04* *(0.0024)*			
AR(2) TEST (p-value)	-1.00 (0.3196) *-0.54* *(0.5877)*	-1.71 (0.0866) *-0.90* *(0.3661)*	-1.98 (0.0478) *-1.15* *(0.2488)*	-0.62 (0.5348) *-0.36* *(0.7177)*	-1.51 (0.1307) *-0.83* *(0.4061)*	-1.81 (0.0703) *-1.05* *(0.2932)*	-0.64 (0.5217) *-0.37* *(0.7080)*	-1.08 (0.2820) *-0.60* *(0.5505)*	-1.27 (0.2034) *-0.76* *(0.4488)*			

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.21: Short Run GMM: Dependent Variable is NGE1 and Independent Variables are EMN and EGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
$NGE1_{i,t-1}$	0.7220 (0.1354)*** (0.1248)***	0.8090 (0.1496)*** (0.1637)***	0.8863 (0.1751)*** (0.1895)***	0.8326 (0.1602)*** (0.1553)***	0.4428 (0.1134)*** (0.1089)***	0.4213 (0.1616)*** (0.2213)*	0.8360 (0.1600)*** (0.1553)***	0.4375 (0.1134)*** (0.1064)***	0.4019 (0.1615)** (0.2165)*	0.5717 (0.1233)*** (0.1644)***	0.3222 (0.0958)*** (0.1240)***	0.4142 (0.1248)*** (0.1246)***
NMN_{it} $NMN_{i,t-1}$	0.0061 (0.0022)*** (0.0031)* -0.0009 (0.0025) (0.0029)	-0.0023 (0.0038) (0.0051) -0.0055 (0.0061) (0.0051)	0.0038 (0.0061) (0.0087) -0.0197 (0.0110)* (0.0087)**	0.0091 (0.0026)*** (0.0037)** -0.0045 (0.0034) (0.0045)	0.0127 (0.0050)** (0.0052)** -0.0057 (0.0058) (0.0065)	0.0147 (0.0070)** (0.0064)** -0.0076 (0.0069) (0.0078)	0.0090 (0.0027)*** (0.0038)** -0.0048 (0.0034) (0.0046)	0.0143 (0.0049)*** (0.0048)*** -0.0072 (0.0056) (0.0059)	0.0169 (0.0068)** (0.0058)*** -0.0087 (0.0066) (0.0069)	0.0094 (0.0030)*** (0.0045)** -0.0066 (0.0030)** (0.0043)	0.0190 (0.0048)*** (0.0063)*** -0.0134 (0.0043)*** (0.0054)**	0.0171 (0.0056)*** (0.0066)** -0.0140 (0.0054)** (0.0061)**
EMN_{it} $EMN_{i,t-1}$				0.0999 (0.0579)* (0.0618) -0.1644 (0.0605)*** (0.0555)***	0.1921 (0.0788)** (0.0943)** -0.1322 (0.0620)** (0.0577)**	0.2511 (0.1074)** (0.1097)** -0.1241 (0.0894) (0.1015)	0.0974 (0.0579)* (0.0608) -0.1670 (0.0611)*** (0.0570)***	0.2049 (0.0784)*** (0.0931)** -0.1469 (0.0618)** (0.0559)***	0.2688 (0.1084)** (0.1089)** -0.1400 (0.0888) (0.0929)	0.1371 (0.0523)*** (0.0531)** -0.1621 (0.0525)*** (0.0595)***	0.2248 (0.0682)*** (0.0766)*** -0.2169 (0.0568)*** (0.0627)***	0.2318 (0.0840)*** (0.0850)*** -0.2059 (0.0738)*** (0.0684)***
$EGE1_{it}$ $EGE1_{i,t-1}$				0.0388 (0.0405) (0.0299) -0.0855 (0.0422)** (0.0302)***	0.1078 (0.0516)** (0.0414)*** -0.0444 (0.0437) (0.0295)	0.1162 (0.0723) (0.0635)* -0.0515 (0.0614) (0.0640)	0.0293 (0.0413) (0.0286) -0.0863 (0.0423)** (0.0301)***	0.1045 (0.0528)** (0.0413)** -0.0467 (0.0438) (0.0288)	0.1131 (0.0731) (0.0627)* -0.0528 (0.0617) (0.0627)	0.0485 (0.0335) (0.0253)* -0.0851 (0.0343)** (0.0286)***	0.0493 (0.0456) (0.0374) -0.0675 (0.0372)* (0.0288)**	0.0602 (0.0602) (0.0573) -0.0754 (0.0569) (0.0456)*
AGE_{it} $AGE_{i,t-1}$							0.0047 (0.0057) (0.0058) 0.0033 (0.0040) (0.0031)	0.0056 (0.0052) (0.0058) -0.0003 (0.0032) (0.0027)	0.0063 (0.0057) (0.0063) 0.0005 (0.0034) (0.0029)	0.0092 (0.0052)* (0.0058) 0.0026 (0.0033) (0.0027)	0.0115 (0.0052)** (0.0059)* -0.0013 (0.0028) (0.0027)	0.0130 (0.0059)** (0.0064)** 0.0004 (0.0031) (0.0028)
$ECACRF_{it}$ $ECACRF_{i,t-1}$										-0.0026 (0.0020) (0.0020) -0.0073 (0.0021)*** (0.0020)***	-0.0025 (0.0030) (0.0026) -0.0082 (0.0029)*** (0.0032)**	-0.0049 (0.0036) (0.0034) -0.0036 (0.0046) (0.0040)
OBS.	400			392			392			325		
SARGAN TEST (p-value)	10.84 (0.2871)	16.09 (0.5175)	9.96 (0.6974)	8.88 (0.4484)	43.72 (0.1005)	38.10 (0.0126)	8.68 (0.4674)	42.85 (0.1170)	37.38 (0.0152)	4.75 (0.8557)	49.94 (0.1597)	26.57 (0.3776)
AR(1) TEST (p-value)	-5.57 (0.0000) -4.78 (0.0000)	-5.32 (0.0000) -4.46 (0.0000)	-5.16 (0.0000) -4.48 (0.0000)	-5.28 (0.0000) -4.60 (0.0000)	-5.07 (0.0000) -4.46 (0.0000)	-3.40 (0.0007) -2.56 (0.0105)	-5.32 (0.0000) -4.58 (0.0000)	-5.10 (0.0000) -4.37 (0.0000)	-3.30 (0.0010) -2.59 (0.0095)	-5.12 (0.0000) -3.50 (0.0005)	-5.24 (0.0000) -3.35 (0.0004)	-4.40 (0.0010) -3.79 (0.0002)
AR(2) TEST (p-value)	-1.79 (0.0739) -1.07 (0.2851)	-1.72 (0.0848) -1.07 (0.2836)	-1.44 (0.1500) -0.99 (0.3234)	-2.10 (0.0355) -1.31 (0.1895)	-2.95 (0.0032) -1.65 (0.0988)	-2.53 (0.0113) -1.54 (0.1244)	-2.04 (0.0411) -1.26 (0.2077)	-2.91 (0.0036) -1.60 (0.1087)	-2.46 (0.0140) -1.47 (0.1429)	-1.19 (0.2356) -0.73 (0.4633)	-0.76 (0.4468) -0.57 (0.5656)	-0.49 (0.6217) -0.37 (0.7088)

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.22: Short Run GMM: Dependent Variable is NGE1 and Independent Variables are AMN and AGE1

	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
$NGE1_{i,t-1}$	0.7220 (0.1354)*** (0.1248)***	0.8090 (0.1496)*** (0.1637)***	0.8863 (0.1751)*** (0.1895)***	0.5620 (0.1356)*** (0.1337)***	0.3766 (0.1297)*** (0.1362)***	0.4541 (0.1873)** (0.2123)**	0.5617 (0.1354)*** (0.1306)***	0.3354 (0.1281)*** (0.1387)**	0.4501 (0.1868)** (0.2120)**	0.3901 (0.1188)*** (0.1419)***	0.1739 (0.1109) (0.1283)	0.1569 (0.1572) (0.1701)
NMN_{it} $NMN_{i,t-1}$	0.0061 (0.0022)*** (0.0031)* -0.0009 (0.0025) (0.0029)	-0.0023 (0.0038) (0.0051) -0.0055 (0.0061) (0.0051)	0.0038 (0.0061) (0.0087) -0.0197 (0.0110)* (0.0087)**	0.0053 (0.0022)** (0.0029)* 0.0012 (0.0026) (0.0030)	0.0001 (0.0027) (0.0025) 0.0017 (0.0033) (0.0031)	0.0001 (0.0036) (0.0037) 0.0009 (0.0039) (0.0036)	0.0049 (0.0022)** (0.0029)* 0.0012 (0.0026) (0.0030)	0.0001 (0.0027) (0.0024) 0.0022 (0.0033) (0.0032)	-0.0005 (0.0037) (0.0036) 0.0015 (0.0040) (0.0036)	0.0037 (0.0024) (0.0029) -0.0007 (0.0024) (0.0027)	-0.0017 (0.0026) (0.0028) -0.0005 (0.0026) (0.0032)	-0.0020 (0.0029) (0.0028) -0.0016 (0.0032) (0.0033)
AMN_{it} $AMN_{i,t-1}$				0.0117 (0.0082) (0.0064)* 0.0005 (0.0103) (0.0078)	0.0117 (0.0121) (0.0117) 0.0125 (0.0151) (0.0151)	0.0060 (0.0146) (0.0125) 0.0239 (0.0176) (0.0198)	0.0129 (0.0082) (0.0065)** 0.0023 (0.0104) (0.0076)	0.0110 (0.0119) (0.0118) 0.0120 (0.0148) (0.0156)	0.0082 (0.0148) (0.0127) 0.0219 (0.0175) (0.0201)	0.0108 (0.0071) (0.0059)* 0.0036 (0.0086) (0.0068)	0.0016 (0.0091) (0.0098) 0.0142 (0.0117) (0.0124)	-0.0036 (0.0115) (0.0110) 0.0211 (0.0134) (0.0147)
$AGE1_{it}$ $AGE1_{i,t-1}$				-0.1072 (0.5661) (0.6053) 1.0688 (0.7653) (0.6399)*	1.9254 (1.2142) (1.4418) 1.2950 (1.2342) (1.1259)	1.9692 (1.6500) (1.5675) 0.5630 (1.7321) (1.4176)	-0.1333 (0.5681) (0.6254) 0.9577 (0.7674) (0.6197)	2.0079 (1.2230) (1.4962) 1.5347 (1.1868) (1.1357)	1.9063 (1.6575) (1.5520) 0.4004 (1.7324) (1.4069)	-0.4050 (0.4975) (0.4050) 0.5978 (0.6392) (0.4864)	1.0425 (0.8810) (1.0078) 1.0709 (0.8388) (0.8552)	1.5821 (1.2145) (1.1495) 0.3965 (1.1450) (1.0166)
AGE_{it} $AGE_{i,t-1}$							0.0023 (0.0057) (0.0061) 0.0048 (0.0038) (0.0029)	-0.0002 (0.0053) (0.0060) 0.0057 (0.0035) (0.0027)**	-0.0001 (0.0057) (0.0061) 0.0063 (0.0038)* (0.0027)**	0.0064 (0.0054) (0.0070) 0.0049 (0.0033) (0.0026)*	0.0044 (0.0051) (0.0066) 0.0051 (0.0030)* (0.0026)*	0.0037 (0.0057) (0.0061) 0.0050 (0.0031) (0.0028)*
$ECACRF_{it}$ $ECACRF_{i,t-1}$										-0.0028 (0.0020) (0.0018) -0.0072 (0.0022)*** (0.0022)***	-0.0025 (0.0037) (0.0032) -0.0104 (0.0037)*** (0.0040)***	-0.0044 (0.0044) (0.0038) -0.0110 (0.0053)** (0.0049)**
OBS.	400			348			348			285		
SARGAN TEST (p-value)	10.84 (0.2871)	16.09 (0.5175)	9.96 (0.6974)	13.92 (0.1251)	33.86 (0.4257)	26.93 (0.1733)	13.80 (0.1297)	35.78 (0.3391)	27.57 (0.1527)	8.31 (0.5033)	46.73 (0.2486)	33.74 (0.1135)
AR(1) TEST (p-value)	-5.57 (0.0000) -4.78 (0.0000)	-5.32 (0.0000) -4.46 (0.0000)	-5.16 (0.0000) -4.48 (0.0000)	-4.60 (0.0000) -4.16 (0.0000)	-3.88 (0.0001) -3.21 (0.0013)	-3.19 (0.0014) -2.71 (0.0067)	-4.62 (0.0000) -4.23 (0.0000)	-3.69 (0.0002) -3.08 (0.0021)	-3.19 (0.0014) -2.74 (0.0061)	-4.26 (0.0000) -3.59 (0.0003)	-3.60 (0.0003) -3.52 (0.0004)	-2.57 (0.0101) -2.69 (0.0072)
AR(2) TEST (p-value)	-1.79 (0.0739) -1.07 (0.2851)	-1.72 (0.0848) -1.07 (0.2836)	-1.44 (0.1500) -0.99 (0.3234)	-2.09 (0.0363) -1.27 (0.2036)	-2.02 (0.0429) -1.24 (0.2142)	-1.78 (0.0752) -1.19 (0.2328)	-2.11 (0.0352) -1.27 (0.2045)	-2.19 (0.0286) -1.34 (0.1803)	-1.77 (0.0771) -1.17 (0.2440)	-1.35 (0.1779) -0.75 (0.4536)	-2.21 (0.0268) -1.18 (0.2392)	-2.10 (0.0355) -1.17 (0.2411)

Note: (*), (**) and (***) indicates significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.23: Short Run GMM: Dependent Variable is EGE1 and Independent Variables are IMN and IGE1

	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
$EGE1_{i,t-1}$	0.5335 (0.0692)*** (0.1546)***	0.4642 (0.0662)*** (0.1592)***	0.4850 (0.0690)*** (0.1641)***	0.4597 (0.0689)*** (0.1410)***	0.3207 (0.0668)*** (0.1225)***	0.2847 (0.0737)*** (0.1130)**	0.4445 (0.0682)*** (0.1414)***	0.3100 (0.0660)*** (0.1212)**	0.2818 (0.0733)*** (0.1128)**	0.4408 (0.0681)*** (0.1417)***	0.3349 (0.0649)*** (0.1152)***	0.2785 (0.0725)*** (0.1087)**
EMN_{it} $EMN_{i,t-1}$	-1.0509 (0.0455)*** (0.0777)*** 0.5066 (0.0847)*** (0.1786)***	-1.0173 (0.0651)*** (0.1005)*** 0.3125 (0.0928)*** (0.1642)*	-1.1366 (0.0803)*** (0.1448)*** 0.2524 (0.1125)** (0.2146)	-1.2015 (0.0554)*** (0.0941)*** 0.4814 (0.0897)*** (0.1564)***	-1.3466 (0.0861)*** (0.1468)*** 0.3980 (0.0967)*** (0.1254)***	-1.2691 (0.1208)*** (0.1537)*** 0.2280 (0.1191)* (0.1502)	-1.1632 (0.0573)*** (0.0927)*** 0.4678 (0.0891)*** (0.1532)***	-1.2938 (0.0886)*** (0.1312)*** 0.3808 (0.0964)*** (0.1220)***	-1.2546 (0.1252)*** (0.1478)*** 0.2310 (0.1190)* (0.1465)	-1.1524 (0.0578)*** (0.0931)*** 0.4609 (0.0892)*** (0.1536)***	-1.2765 (0.0861)*** (0.1183)*** 0.3945 (0.0978)*** (0.1126)***	-1.2641 (0.1158)*** (0.1336)*** 0.2242 (0.1181)* (0.1442)
IMN_{it} $IMN_{i,t-1}$				-0.0231 (0.0058)*** (0.0069)*** 0.0258 (0.0073)*** (0.0081)***	-0.0512 (0.0109)*** (0.0158)*** 0.0313 (0.0131)** (0.0136)**	-0.0444 (0.0152)*** (0.0187)** 0.0197 (0.0157) (0.0149)	-0.0218 (0.0058)*** (0.0071)*** 0.0214 (0.0075)*** (0.0080)***	-0.0472 (0.0110)*** (0.0137)*** 0.0235 (0.0129)* (0.0121)*	-0.0439 (0.0157)*** (0.0181)** 0.0184 (0.0154) (0.0146)	-0.0211 (0.0059)*** (0.0071)*** 0.0225 (0.0076)*** (0.0081)***	-0.0469 (0.0105)*** (0.0124)*** 0.0198 (0.0132) (0.0105)*	-0.0422 (0.0144)*** (0.0144)*** 0.0195 (0.0151) (0.0135)
$IGE1_{it}$ $IGE1_{i,t-1}$				0.4930 (0.1224)*** (0.1648)*** 0.0788 (0.1298) (0.0963)	0.8107 (0.2616)*** (0.3747)** 0.4931 (0.2907)* (0.4405)	1.4792 (0.3491)*** (0.5037)*** 0.3759 (0.3820) (0.5096)	0.4699 (0.1215)*** (0.1575)*** 0.0897 (0.1285) (0.0987)	0.8487 (0.2632)*** (0.3412)** 0.4694 (0.2835)* (0.4103)	1.4920 (0.3535)*** (0.4998)*** 0.3459 (0.3799) (0.5017)	0.4557 (0.1227)*** (0.1507)*** 0.0569 (0.1338) (0.0949)	0.8935 (0.2471)*** (0.3388)*** 0.3063 (0.2846) (0.4291)	1.4805 (0.3251)*** (0.4557)*** 0.4375 (0.3757) (0.4791)
AGE_{it} $AGE_{i,t-1}$							0.0121 (0.0080) (0.0088) 0.0125 (0.0056)** (0.0072)*	0.0029 (0.0089) (0.0085) 0.0092 (0.0053)* (0.0072)	0.0033 (0.0099) (0.0102) 0.0080 (0.0059) (0.0071)	0.0109 (0.0081) (0.0086) 0.0128 (0.0056)** (0.0072)*	0.0005 (0.0091) (0.0089) 0.0098 (0.0056)* (0.0071)	0.0043 (0.0099) (0.0092) 0.0053 (0.0062) (0.0075)
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										-0.1522 (0.2360) (0.1955) -0.1322 (0.2059) (0.2219)	-0.5413 (0.5874) (0.6106) 0.6144 (0.3475)* (0.3533)*	0.6687 (0.7495) (0.7166) 0.0164 (0.6458) (0.8318)
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$												

$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	392			392			392			392		
SARGAN TEST (p-value)	70.04 (0.0000)	106.35 (0.0000)	72.33 (0.0000)	74.97 (0.0000)	108.10 (0.0000)	54.85 (0.0001)	73.50 (0.0000)	108.69 (0.0000)	54.10 (0.0001)	73.69 (0.0000)	117.15 (0.0000)	59.63 (0.0001)
AR(1) TEST (p-value)	-7.26 (0.0000) *-3.57* *(0.0004)*	-7.16 (0.0000) *-3.53* *(0.0004)*	-6.58 (0.0000) *-3.28* *(0.0010)*	-6.50 (0.0000) *-3.76* *(0.0002)*	-3.94 (0.0001) *-2.75* *(0.0060)*	-2.18 (0.0290) *-1.70* *(0.0893)*	-6.36 (0.0000) *-3. 61* *(0.0003)*	-3.76 (0.0002) *-2.55* *(0.0108)*	-2.18 (0.0296) *-1.68* *(0.0926)*	-6.40 (0.0000) *-3. 53* *(0.0004)*	-3.96 (0.0001) *-2.93* *(0.0034)*	-2.49 (0.0127) *-2.18* *(0.0292)*
AR(2) TEST (p-value)	-0.47 (0.6394) *-0.93* *(0.3544)*	-0.64 (0.5222) *-1.18* *(0.2395)*	-0.93 (0.3548) *-1.30* *(0.1926)*	0.30 (0.7629) *0.59* *(0.5541)*	1.03 (0.3017) *1.42* *(0.1553)*	0.91 (0.3614) *1.27* *(0.2046)*	0.81 (0.4171) *1.61* *(0.1067)*	1.15 (0.2510) *1.68* *(0.0923)*	1.05 (0.2935) *1.43* *(0.1516)*	0.72 (0.4737) *1.38* *(0.1685)*	0.49 (0.6268) *0.73* *(0.4645)*	1.19 (0.2321) *1.39* *(0.1645)*

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous			
$EGE1_{i,t-1}$	0.3233 (0.0756)*** *(0.1538)*****	0.3432 (0.0708)*** *(0.1234)*******	0.2445 (0.0766)*** *(0.1053)*****	0.3520 (0.0768)*** *(0.1592)*****	0.3291 (0.0636)*** *(0.0919)*******	0.2338 (0.0723)*** *(0.0868)*******	0.3547 (0.0763)*** *(0.1568)*****	0.3368 (0.0661)*** *(0.1222)*******	0.2049 (0.0830)** *(0.1295)*			
EMN_{it} $EMN_{i,t-1}$	-1.2725 (0.0646)*** *(0.0935)******* 0.3757 (0.1038)*** *(0.1830)*****	-1.2377 (0.1073)*** *(0.1337)******* 0.3393 (0.1100)*** *(0.1614)*****	-1.2496 (0.1271)*** *(0.1424)******* 0.2601 (0.1187)** *(0.1368)****	-1.2625 (0.0656)*** *(0.0931)******* 0.4047 (0.1063)*** *(0.1898)*****	-1.2235 (0.0930)*** *(0.1148)******* 0.3285 (0.1046)*** *(0.1160)*******	-1.2610 (0.1147)*** *(0.1208)******* 0.2387 (0.1176)** *(0.1080)*****	-1.2586 (0.0657)*** *(0.0916)******* 0.4187 (0.1058)*** *(0.1898)*****	-1.1803 (0.0918)*** *(0.1126)******* 0.3245 (0.1044)*** *(0.1513)*****	-1.1968 (0.1311)*** *(0.1315)******* 0.1583 (0.1358) *(0.1697)*			
IMN_{it} $IMN_{i,t-1}$	-0.0252 (0.0079)*** *(0.0089)******* 0.0263 (0.0081)*** *(0.0090)*******	-0.0195 (0.0134) *(0.0144)* 0.0358 (0.0131)*** *(0.0147)*****	-0.0312 (0.0160)* *(0.0163)**** 0.0373 (0.0150)** *(0.0159)*****	-0.0251 (0.0080)*** *(0.0090)******* 0.0236 (0.0082)*** *(0.0085)*******	-0.0206 (0.0125)* *(0.0136)* 0.0259 (0.0116)** *(0.0115)*****	-0.0352 (0.0151)** *(0.0145)***** 0.0333 (0.0140)** *(0.0133)*****	-0.0259 (0.0081)*** *(0.0098)******* 0.0250 (0.0083)*** *(0.0090)*******	-0.0155 (0.0123) *(0.0109)* 0.0228 (0.0114)** *(0.0120)****	-0.0194 (0.0174) *(0.0159)* 0.0192 (0.0157) *(0.0147)*			
$IGE1_{it}$ $IGE1_{i,t-1}$	0.4146 (0.1400)*** *(0.1436)******* 0.0725 (0.1399) *(0.0951)*	0.6213 (0.2781)** *(0.2820)***** -0.3497 (0.2747) *(0.2424)*	0.9512 (0.3957)** *(0.3670)***** -0.1977 (0.3485) *(0.4414)*	0.4672 (0.1396)*** *(0.1666)******* 0.1076 (0.1415) *(0.0977)*	0.4778 (0.2297)** *(0.2068)***** 0.0774 (0.2312) *(0.1704)*	0.9362 (0.3409)*** *(0.2995)******* 0.0603 (0.2970) *(0.3353)*	0.4757 (0.1404)*** *(0.1661)******* 0.0728 (0.1484) *(0.0995)*	0.4433 (0.2576)* *(0.2558)**** -0.0268 (0.2695) *(0.2051)*	0.7412 (0.4151)* *(0.3845)**** 0.0655 (0.3683) *(0.3751)*			
AGE_{it} $AGE_{i,t-1}$	0.0038 (0.0091) *(0.0098)* 0.0125 (0.0058)** *(0.0068)****	0.0118 (0.0108) *(0.0118)* 0.0090 (0.0062) *(0.0080)*	0.0015 (0.0112) *(0.0108)* 0.0089 (0.0062) *(0.0075)*	0.0067 (0.0092) *(0.0099)* 0.0124 (0.0059)** *(0.0072)****	0.0161 (0.0100) *(0.0118)* 0.0097 (0.0058)* *(0.0082)*	0.0053 (0.0111) *(0.0132)* 0.0088 (0.0062) *(0.0081)*	0.0049 (0.0096) *(0.0103)* 0.0135 (0.0059)** *(0.0071)****	0.0236 (0.0115)** *(0.0137)**** 0.0099 (0.0063) *(0.0070)*	0.0257 (0.0145)* *(0.0150)**** 0.0095 (0.0074) *(0.0085)*			

$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	-0.0127 (0.0041)*** (0.0063)** -0.0038 (0.0043) (0.0039)	-0.0309 (0.0070)*** (0.0106)*** 0.0052 (0.0071) (0.0059)	-0.0230 (0.0088)*** (0.0127)* -0.0099 (0.0091) (0.0085)									
$UNEM_{it}$ $UNEM_{i,t-1}$				0.2051 (0.3987) (0.3053) -0.5709 (0.3817) (0.3558)	0.5696 (0.7011) (0.8967) -1.5064 (0.5138)*** (0.5788)***	1.3752 (0.8235)* (0.8543) -0.9583 (0.7835) (0.7173)						
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$							0.0463 (0.3153) (0.2198) 0.1294 (0.2602) (0.3095)	-1.3642 (0.6882)** (0.6459)** 0.0047 (0.3674) (0.4255)	-2.6741 (1.0069)*** (0.8799)*** -1.0835 (0.8268) (0.7037)			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				-0.0091 (0.0035)** (0.0050)* -0.0015 (0.0038) (0.0040)	-0.0188 (0.0056)*** (0.0093)** 0.0025 (0.0058) (0.0045)	-0.0155 (0.0069)** (0.0107) -0.0083 (0.0078) (0.0074)	-0.0086 (0.0036)** (0.0050)* -0.0017 (0.0038) (0.0042)	-0.0222 (0.0069)*** (0.0100)** 0.0038 (0.0060) (0.0045)	-0.0297 (0.0109)*** (0.0111)*** -0.0178 (0.0099)* (0.0105)*			
OBS.	325			325			325					
SARGAN TEST (p-value)	50.77 (0.0000)	100.02 (0.0000)	62.18 (0.0001)	54.42 (0.0000)	124.77 (0.0000)	71.76 (0.0000)	52.44 (0.0000)	124.48 (0.0000)	56.30 (0.0017)			
AR(1) TEST (p-value)	-4.34 (0.0000) -3. 25 (0.0012)	-4.90 (0.0000) -4.23 (0.0000)	-3.31 (0.0009) -2.63 (0.0085)	-4.44 (0.0000) -3. 06 (0.0022)	-4.78 (0.0000) -3.86 (0.0001)	-3.32 (0.0009) -2.42 (0.0154)	-4.66 (0.0000) -3. 26 (0.0011)	-5.68 (0.0000) -4.19 (0.0000)	-2.81 (0.0050) -2.12 (0.0336)			
AR(2) TEST (p-value)	1.09 (0.2739) 1.85 (0.0644)	0.51 (0.6083) 0.68 (0.4956)	1.26 (0.2067) 1.52 (0.1281)	0.85 (0.3968) 1.48 (0.1394)	0.40 (0.6877) 0.60 (0.5464)	0.95 (0.3396) 1.08 (0.2815)	1.07 (0.2848) 2.02 (0.0434)	0.97 (0.3338) 1.65 (0.0986)	0.94 (0.3482) 1.17 (0.2408)			

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**),and (***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.24: Short Run GMM: Dependent Variable is EGE1 and Independent Variables are NMN and NGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
$EGE1_{i,t-1}$	0.5335 (0.0692)*** *(0.1546)******	0.4642 (0.0662)*** *(0.1592)******	0.4850 (0.0690)*** *(0.1641)******	0.5098 (0.0697)*** *(0.1512)******	0.3909 (0.0680)*** *(0.1415)******	0.3244 (0.0796)*** *(0.1563)*****	0.4941 (0.0685)*** *(0.1497)******	0.3842 (0.0671)*** *(0.1380)******	0.3276 (0.0779)*** *(0.1553)*****	0.4902 (0.0692)*** *(0.1537)******	0.3628 (0.0667)*** *(0.1325)******	0.3011 (0.0764)*** *(0.1417)*****
EMN_{it} $EMN_{i,t-1}$	-1.0509 (0.0455)*** *(0.0777)****** 0.5066 (0.0847)*** *(0.1786)******	-1.0173 (0.0651)*** *(0.1005)****** 0.3125 (0.0928)*** *(0.1642)****	-1.1366 (0.0803)*** *(0.1448)****** 0.2524 (0.1125)** *(0.2146)*	-1.1655 (0.0551)*** *(0.0992)****** 0.5273 (0.0921)*** *(0.1698)******	-1.1766 (0.0961)*** *(0.1504)****** 0.3903 (0.1080)*** *(0.1706)*****	-1.2484 (0.1324)*** *(0.1934)****** 0.2399 (0.1450)* *(0.2101)*	-1.1350 (0.0557)*** *(0.0938)****** 0.5162 (0.0912)*** *(0.1639)******	-1.1470 (0.0961)*** *(0.1353)****** 0.3794 (0.1072)*** *(0.1608)*****	-1.2628 (0.1330)*** *(0.1855)****** 0.2693 (0.1428)* *(0.2030)*	-1.1273 (0.0598)*** *(0.0973)****** 0.5105 (0.0924)*** *(0.1696)******	-1.1749 (0.0946)*** *(0.1254)****** 0.3729 (0.1072)*** *(0.1544)*****	-1.2246 (0.1318)*** *(0.1511)****** 0.2464 (0.1397)* *(0.1886)*
NMN_{it} $NMN_{i,t-1}$				-0.0114 (0.0040)*** *(0.0036)****** 0.0144 (0.0050)*** *(0.0057)*****	-0.0214 (0.0092)** *(0.0111)**** 0.0125 (0.0103) *(0.0111)*	-0.0185 (0.0132) *(0.0144)* -0.0017 (0.0126) *(0.0116)*	-0.0117 (0.0040)*** *(0.0039)****** 0.0126 (0.0050)** *(0.0052)*****	-0.0205 (0.0090)** *(0.0099)***** 0.0108 (0.0098) *(0.0093)*	-0.0216 (0.0132) *(0.0136)* 0.0002 (0.0122) *(0.0106)*	-0.0116 (0.0042)*** *(0.0041)****** 0.0123 (0.0053)** *(0.0050)*****	-0.0238 (0.0082)*** *(0.0091)****** 0.0108 (0.0101) *(0.0088)*	-0.0198 (0.0124) *(0.0106)**** -0.0002 (0.0121) *(0.0085)******
$NGE1_{it}$ $NGE1_{i,t-1}$				0.3040 (0.1082)*** *(0.1239)***** 0.0553 (0.1181) *(0.0799)*	0.8430 (0.2529)*** *(0.3465)***** 0.1706 (0.2304) *(0.2993)*	1.2627 (0.3344)*** *(0.5372)***** 0.7696 (0.3204)** *(0.5134)*	0.2754 (0.1066)** *(0.1123)***** 0.0602 (0.1161) *(0.0802)*	0.8021 (0.2515)*** *(0.3279)***** 0.1653 (0.2259) *(0.2899)*	1.1959 (0.3266)*** *(0.5161)***** 0.7553 (0.3122)** *(0.4927)*	0.2742 (0.1086)** *(0.1053)****** 0.0573 (0.1177) *(0.0767)*	0.7768 (0.2259)*** *(0.3032)***** 0.2403 (0.2260) *(0.3614)*	1.0463 (0.2968)*** *(0.4148)***** 0.6284 (0.3227)* *(0.4302)*
AGE_{it} $AGE_{i,t-1}$							0.0152 (0.0082)* *(0.0086)**** 0.0150 (0.0057)*** *(0.0070)*****	0.0126 (0.0091) *(0.0087)* 0.0084 (0.0054) *(0.0069)*	0.0100 (0.0107) *(0.0097)* 0.0080 (0.0064) *(0.0071)*	0.0144 (0.0083)* *(0.0085)**** 0.0146 (0.0057)** *(0.0071)*****	0.0108 (0.0090) *(0.0090)* 0.0100 (0.0056)* *(0.0075)*	0.0075 (0.0104) *(0.0090)* 0.0089 (0.0067) *(0.0082)*
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										0.0734 (0.2511) *(0.2074)* -0.0374 (0.2131) *(0.2242)*	-0.4761 (0.5854) *(0.4459)* 0.2055 (0.3912) *(0.5273)*	-0.6317 (0.8010) *(0.7404)* -0.6421 (0.6573) *(0.8952)*
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$												

$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	392			392			392			392		
SARGAN TEST (p-value)	70.04 (0.0000)	106.35 (0.0000)	72.33 (0.0000)	70.79 (0.0000)	111.11 (0.0000)	45.76 (0.0014)	69.23 (0.0000)	111.22 (0.0000)	46.27 (0.0012)	74.21 (0.0000)	123.38 (0.0000)	49.96 (0.0022)
AR(1) TEST (p-value)	-7.26 (0.0000) *-3.57* *(0.0004)*	-7.16 (0.0000) *-3.53* *(0.0004)*	-6.58 (0.0000) *-3.28* *(0.0010)*	-6.80 (0.0000) *-3.60* *(0.0003)*	-4.77 (0.0000) *-2.71* *(0.0066)*	-1.58 (0.1148) *-1.01* *(0.3126)*	-6.63 (0.0000) *-3.48* *(0.0005)*	-4.88 (0.0000) *-2.71* *(0.0068)*	-1.60 (0.1098) *-1.01* *(0.3122)*	-6.69 (0.0000) *-3.38* *(0.0007)*	-4.46 (0.0000) *-2.46* *(0.0138)*	-1.51 (0.1313) *-0.99* *(0.3203)*
AR(2) TEST (p-value)	-0.47 (0.6394) *-0.93* *(0.3544)*	-0.64 (0.5222) *-1.18* *(0.2395)*	-0.93 (0.3548) *-1.30* *(0.1926)*	-0.72 (0.4745) *-1.19* *(0.2345)*	-1.20 (0.2308) *-1.65* *(0.0980)*	-1.62 (0.1053) *-1.74* *(0.0825)*	0.05 (0.9625) *0.09* *(0.9293)*	-0.64 (0.5206) *-0.90* *(0.3671)*	-1.14 (0.2551) *-1.24* *(0.2165)*	0.11 (0.9089) *0.21* *(0.8369)*	-0.85 (0.3951) *-1.26* *(0.2064)*	-1.42 (0.1545) *-1.74* *(0.0815)*

	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			
$EGE1_{i,t-1}$	0.3735 (0.0773)*** *(0.1754)*****	0.3548 (0.0749)*** *(0.1499)*****	0.3281 (0.0855)*** *(0.1468)*****	0.4083 (0.0793)*** *(0.1810)*****	0.3439 (0.0707)*** *(0.1255)*******	0.3124 (0.0790)*** *(0.1167)*******	0.4145 (0.0775)*** *(0.1832)*****	0.3621 (0.0702)*** *(0.1516)*****	0.2905 (0.0861)*** *(0.1598)****			
EMN_{it} $EMN_{i,t-1}$	-1.2523 (0.0635)*** *(0.0968)******* 0.4448 (0.1090)*** *(0.2080)*****	-1.1486 (0.1112)*** *(0.1256)******* 0.3613 (0.1283)*** *(0.1984)****	-1.2851 (0.1413)*** *(0.1616)******* 0.4013 (0.1481)*** *(0.2241)****	-1.2465 (0.0657)*** *(0.0978)******* 0.4796 (0.1132)*** *(0.2160)*****	-1.0797 (0.1094)*** *(0.1004)******* 0.3076 (0.1279)** *(0.1549)*****	-1.1948 (0.1312)*** *(0.1222)******* 0.3239 (0.1428)** *(0.1572)*****	-1.2563 (0.0664)*** *(0.0986)******* 0.4954 (0.1109)*** *(0.2204)*****	-1.1822 (0.0996)*** *(0.1139)******* 0.3825 (0.1191)*** *(0.1888)*****	-1.2450 (0.1281)*** *(0.1296)******* 0.3051 (0.1520)** *(0.2267)*			
NMN_{it} $NMN_{i,t-1}$	-0.0168 (0.0056)*** *(0.0057)******* 0.0158 (0.0054)*** *(0.0058)*******	-0.0119 (0.0107) *(0.0099)* 0.0167 (0.0093)* *(0.0085)*****	-0.0249 (0.0135)* *(0.0137)**** 0.0297 (0.0126)** *(0.0131)*****	-0.0162 (0.0057)*** *(0.0056)******* 0.0139 (0.0056)** *(0.0056)*****	-0.0063 (0.0107) *(0.0089)* 0.0061 (0.0094) *(0.0066)*	-0.0165 (0.0122) *(0.0097)**** 0.0167 (0.0115) *(0.0088)****	-0.0178 (0.0058)*** *(0.0063)******* 0.0163 (0.0056)*** *(0.0057)*******	-0.0157 (0.0097) *(0.0078)***** 0.0160 (0.0087)* *(0.0073)*****	-0.0195 (0.0124) *(0.0107)**** 0.0204 (0.0118)* *(0.0098)*****			
$NGE1_{it}$ $NGE1_{i,t-1}$	0.2913 (0.1360)** *(0.1091)******* -0.0236 (0.1319) *(0.0830)*	0.4707 (0.2795)* *(0.2645)**** -0.1162 (0.2270) *(0.2469)*******	1.1411 (0.4963)** *(0.5730)***** -0.2510 (0.3354) *(0.4423)*	0.3342 (0.1385)** *(0.1201)******* 0.0429 (0.1358) *(0.0878)*	0.2801 (0.2676) *(0.2033)* 0.3023 (0.2171) *(0.2256)*	0.9536 (0.4168)** *(0.3963)***** 0.1633 (0.2939) *(0.3415)*	0.3459 (0.1389)** *(0.1217)******* -0.0103 (0.1354) *(0.0850)*	0.3800 (0.2601) *(0.2051)**** 0.1009 (0.2090) *(0.2124)*	0.6278 (0.4513) *(0.4520)* 0.1518 (0.3097) *(0.3329)*			
AGE_{it} $AGE_{i,t-1}$	0.0051 (0.0093) *(0.0093)* 0.0154 (0.0059)*** *(0.0063)*****	0.0167 (0.0109) *(0.0117)* 0.0095 (0.0058) *(0.0078)*	-0.0014 (0.0133) *(0.0132)* 0.0078 (0.0064) *(0.0077)*	0.0079 (0.0095) *(0.0095)* 0.0143 (0.0060)** *(0.0068)*****	0.0241 (0.0110)** *(0.0116)***** 0.0091 (0.0058) *(0.0080)*	0.0092 (0.0126) *(0.0128)* 0.0073 (0.0063) *(0.0081)*	0.0070 (0.0098) *(0.0098)* 0.0151 (0.0061)** *(0.0064)*****	0.0248 (0.0114)** *(0.0121)***** 0.0101 (0.0060)* *(0.0076)*	0.0232 (0.0149) *(0.0151)* 0.0065 (0.0071) *(0.0082)*			

$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	-0.0135 (0.0042)*** (0.0065)** -0.0043 (0.0044) (0.0046)	-0.0290 (0.0065)*** (0.0105)*** 0.0052 (0.0069) (0.0053)	-0.0229 (0.0084)*** (0.0132)* -0.0064 (0.0096) (0.0088)									
$UNEM_{it}$ $UNEM_{i,t-1}$				0.0547 (0.4177) (0.3154) -0.6754 (0.3951)* (0.4051)*	0.5640 (0.6840) (0.7134) -1.6220 (0.5344)*** (0.6010)***	0.8371 (0.8381) (0.8380) -1.2436 (0.8448) (0.8154)						
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$							-0.2550 (0.3210) (0.2208) 0.1078 (0.2674) (0.3250)	-1.6203 (0.6348)** (0.5373)*** -0.0944 (0.3681) (0.4706)	-2.7970 (0.9919)*** (0.9856)*** -0.2352 (0.8534) (0.7758)			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				-0.0101 (0.0036)*** (0.0053)* -0.0019 (0.0039) (0.0043)	-0.0196 (0.0058)*** (0.0089)** 0.0021 (0.0061) (0.0044)	-0.0163 (0.0068)** (0.0104) -0.0062 (0.0082) (0.0073)	-0.0099 (0.0037)*** (0.0053)* -0.0017 (0.0040) (0.0046)	-0.0220 (0.0067)*** (0.0093)** 0.0029 (0.0060) (0.0046)	-0.0297 (0.0105)*** (0.0111)*** -0.0140 (0.0098) (0.0101)			
OBS.	325			325			325					
SARGAN TEST (p-value)	46.09 (0.0000)	95.06 (0.0000)	56.63 (0.0003)	51.49 (0.0000)	112.41 (0.0000)	71.89 (0.0000)	49.44 (0.0000)	119.00 (0.0000)	59.81 (0.0007)			
AR(1) TEST (p-value)	-4.44 (0.0000) -3.14 (0.0017)	-4.64 (0.0000) -3.37 (0.0002)	-3.33 (0.0009) -2.23 (0.0256)	-4.65 (0.0000) -3.06 (0.0022)	-4.75 (0.0000) -3.59 (0.0003)	-3.44 (0.0006) -2.43 (0.0150)	-4.92 (0.0000) -3.20 (0.0014)	-5.36 (0.0000) -3.64 (0.0003)	-3.19 (0.0014) -2.35 (0.0185)			
AR(2) TEST (p-value)	0.11 (0.9089) 0.18 (0.8543)	-0.47 (0.6351) -0.61 (0.5435)	-0.53 (0.5587) -0.51 (0.6099)	-0.03 (0.9794) -0.05 (0.9634)	-0.31 (0.7583) -0.58 (0.5634)	-1.01 (0.3148) -1.10 (0.2729)	0.17 (0.8670) 0.32 (0.7492)	0.52 (0.6026) 0.86 (0.3923)	0.53 (0.5968) 0.69 (0.4892)			

Note: (*), (**), and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.25: Short Run GMM: Dependent Variable is AGE1 and Independent Variables are IMN and IGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
$AGE1_{i,t-1}$	0.5747 (0.1913)*** (0.2167)***	0.4429 (0.1589)*** (0.2309)*	0.5498 (0.2030)*** (0.2309)**	0.2739 (0.1987) (0.2015)	-0.0465 (0.1520) (0.1794)	-0.1435 (0.1862) (0.1828)	0.2448 (0.1900) (0.1939)	-0.0670 (0.1500) (0.1759)	-0.1511 (0.1835) (0.1763)	0.2551 (0.1893) (0.1936)	-0.0420 (0.1540) (0.1619)	-0.1598 (0.1974) (0.1758)
AMN_{it} $AMN_{i,t-1}$	0.0054 (0.0008)*** (0.0016)*** -0.0070 (0.0016)*** (0.0018)***	0.0030 (0.0013)** (0.0019) -0.0031 (0.0023) (0.0023)	0.0008 (0.0018) (0.0021) -0.0009 (0.0029) (0.0032)	0.0058 (0.0008)*** (0.0016)*** -0.0049 (0.0016)*** (0.0015)***	0.0018 (0.0014) (0.0017) -0.0011 (0.0018) (0.0015)	0.0010 (0.0017) (0.0020) -0.0009 (0.0020) (0.0018)	0.0058 (0.0008)*** (0.0015)*** -0.0047 (0.0016)*** (0.0015)***	0.0019 (0.0014) (0.0016) -0.0007 (0.0018) (0.0016)	0.0010 (0.0017) (0.0019) -0.0006 (0.0020) (0.0018)	0.0058 (0.0008)*** (0.0015)*** -0.0047 (0.0016)*** (0.0015)***	0.0023 (0.0014) (0.0016) -0.0007 (0.0018) (0.0016)	0.0013 (0.0019) (0.0018) -0.0013 (0.0021) (0.0020)
IMN_{it} $IMN_{i,t-1}$				0.0006 (0.0003)* (0.0003)* 0.0003 (0.0004) (0.0004)	0.0004 (0.0004) (0.0007) -0.0002 (0.0005) (0.0006)	0.0003 (0.0005) (0.0007) -0.0002 (0.0006) (0.0007)	0.0007 (0.0003)** (0.0003)** 0.0002 (0.0004) (0.0004)	0.0005 (0.0004) (0.0007) -0.0003 (0.0005) (0.0006)	0.0004 (0.0005) (0.0007) -0.0003 (0.0006) (0.0007)	0.0007 (0.0003)** (0.0003)** 0.0004 (0.0004) (0.0004)	0.0004 (0.0005) (0.0006) -0.0001 (0.0006) (0.0006)	0.0001 (0.0006) (0.0007) 0.0002 (0.0007) (0.0008)
$IGE1_{it}$ $IGE1_{i,t-1}$				0.0020 (0.0091) (0.0057) 0.0098 (0.0088) (0.0105)	0.0415 (0.0193)** (0.0257) 0.0366 (0.0177)** (0.0221)*	0.0644 (0.0269)** (0.0311)** 0.0296 (0.0202) (0.0224)	0.0018 (0.0091) (0.0054) 0.0111 (0.0088) (0.0103)	0.0376 (0.0194)* (0.0240) 0.0385 (0.0174)** (0.0208)*	0.0589 (0.0260)** (0.0307)* 0.0342 (0.0197)* (0.0216)	0.0007 (0.0092) (0.0054) 0.0091 (0.0092) (0.0099)	0.0529 (0.0186)*** (0.0254)** 0.0074 (0.0194) (0.0215)	0.0805 (0.0259)*** (0.0365)** 0.0063 (0.0243) (0.0278)
AGE_{it} $AGE_{i,t-1}$							0.0009 (0.0006) (0.0006) -0.0002 (0.0004) (0.0005)	0.0008 (0.0006) (0.0006) 0.0000 (0.0004) (0.0006)	0.0006 (0.0006) (0.0008) 0.0000 (0.0004) (0.0005)	0.0008 (0.0006) (0.0006) -0.0002 (0.0004) (0.0004)	0.0004 (0.0007) (0.0007) 0.0002 (0.0004) (0.0006)	0.0001 (0.0007) (0.0009) 0.0002 (0.0005) (0.0006)
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										-0.0098 (0.0168) (0.0210) -0.0168 (0.0148) (0.0114)	-0.0725 (0.0359)** (0.0354)** 0.0373 (0.0271) (0.0310)	-0.0887 (0.0453)* (0.0481)* -0.0131 (0.0480) (0.0423)
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$												

$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	348			348			348			348		
SARGAN TEST (p-value)	24.97 (0.0030)	34.76 (0.0067)	20.59 (0.0814)	22.06 (0.0087)	47.89 (0.0453)	31.96 (0.0592)	21.72 (0.0098)	47.42 (0.0498)	31.89 (0.0601)	20.78 (0.0137)	43.81 (0.3531)	27.57 (0.3281)
AR(1) TEST (p-value)	-4.30 (0.0000) *-3.32* *(0.0009)*	-4.18 (0.0000) *-2.37* *(0.0180)*	-4.50 (0.0000) *-2.95* *(0.0031)*	-2.61 (0.0090) *-2.40* *(0.0162)*	-1.37 (0.1694) *-1.02* *(0.3076)*	0.76 (0.4481) *-0.74* *(0.4566)*	-2.58 (0.0098) *-2.41* *(0.0161)*	-1.30 (0.1946) *-0.98* *(0.3268)*	-0.70 (0.4846) *-0.69* *(0.4892)*	-2.55 (0.0107) *-2.38* *(0.0172)*	-2.08 (0.0375) *-1.64* *(0.1005)*	-0.61 (0.5401) *-0.61* *(0.5425)*
AR(2) TEST (p-value)	0.36 (0.7205) *0.42* *(0.6780)*	0.07 (0.9443) *0.08* *(0.9387)*	0.44 (0.6601) *0.47* *(0.6368)*	-0.38 (0.7040) *-0.46* *(0.6466)*	-1.67 (0.0951) *-1.46* *(0.1449)*	-2.00 (0.0453) *-1.79* *(0.0730)*	-0. 82 (0.4144) *-1.02* *(0.3095)*	-2.17 (0.0299) *-1.81* *(0.0698)*	-2.40 (0.0166) *-1.98* *(0.0483)*	-0. 79 (0.4305) *-1.01* *(0.3106)*	-1.02 (0.3078) *-1.05* *(0.2932)*	-0.92 (0.3567) *-0.96* *(0.3392)*

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous			
$AGE1_{i,t-1}$	0.1189 (0.2072) *(0.2010)*	0.1424 (0.1427) *(0.1662)*	0.0156 (0.1704) *(0.1620)*	0.0961 (0.2040) *(0.1983)*	0.1512 (0.1382) *(0.1361)*	0.0123 (0.1648) *(0.1428)*	0.1339 (0.2052) *(0.1983)*	0.1993 (0.1477) *(0.1498)*	0.0860 (0.1619) *(0.1492)*			
AMN_{it} $AMN_{i,t-1}$	0.0050 (0.0009)*** *(0.0016)**** -0.0039 (0.0016)** *(0.0014)****	0.0015 (0.0014) *(0.0015)* -0.0010 (0.0019) *(0.0014)*	0.0011 (0.0018) *(0.0021)* -0.0001 (0.0022) *(0.0018)*	0.0051 (0.0009)*** *(0.0015)**** -0.0040 (0.0016)** *(0.0016)***	0.0025 (0.0014)* *(0.0014)** -0.0017 (0.0020) *(0.0017)*	0.0017 (0.0018) *(0.0019)* -0.0005 (0.0024) *(0.0022)*	0.0051 (0.0009)*** *(0.0015)**** -0.0040 (0.0016)** *(0.0015)****	0.0032 (0.0015)** *(0.0016)*** -0.0020 (0.0019) *(0.0014)*	0.0022 (0.0020) *(0.0022)* -0.0015 (0.0022) *(0.0018)*			
IMN_{it} $IMN_{i,t-1}$	0.0009 (0.0004)** *(0.0005)*** 0.0001 (0.0005) *(0.0004)*	0.0005 (0.0006) *(0.0006)* -0.0006 (0.0006) *(0.0005)*	0.0008 (0.0006) *(0.0008)* -0.0006 (0.0007) *(0.0006)*	0.0010 (0.0004)** *(0.0005)*** 0.0001 (0.0005) *(0.0004)*	0.0005 (0.0006) *(0.0007)* -0.0004 (0.0006) *(0.0005)*	0.0005 (0.0007) *(0.0008)* -0.0004 (0.0006) *(0.0006)*	0.0009 (0.0004)** *(0.0004)*** 0.0002 (0.0005) *(0.0003)*	0.0004 (0.0006) *(0.0005)* -0.0001 (0.0007) *(0.0005)*	0.0007 (0.0006) *(0.0007)* -0.0005 (0.0008) *(0.0007)*			
$IGE1_{it}$ $IGE1_{i,t-1}$	0.0040 (0.0111) *(0.0065)* 0.0188 (0.0102)* *(0.0109)**	0.0216 (0.0244) *(0.0237)* 0.0478 (0.0186)** *(0.0182)****	0.0446 (0.0332) *(0.0327)* 0.0366 (0.0213)* *(0.0206)**	0.0057 (0.0109) *(0.0064)* 0.0193 (0.0102)* *(0.0114)**	0.0159 (0.0195) *(0.0157)* 0.0456 (0.0167)*** *(0.0177)***	0.0346 (0.0268) *(0.0257)* 0.0317 (0.0195) *(0.0192)**	0.0046 (0.0109) *(0.0063)* 0.0178 (0.0105)* *(0.0101)**	0.0062 (0.0230) *(0.0171)* 0.0304 (0.0196) *(0.0169)**	0.0280 (0.0280) *(0.0232)* 0.0288 (0.0216) *(0.0203)*			
AGE_{it}	0.0009 (0.0007) *(0.0008)* -0.0001	0.0010 (0.0008) *(0.0008)* 0.0000	0.0007 (0.0008) *(0.0010)* -0.0001	0.0010 (0.0007) *(0.0007)* -0.0001	0.0009 (0.0008) *(0.0008)* -0.0001	0.0007 (0.0008) *(0.0010)* -0.0001	0.0008 (0.0007) *(0.0007)* -0.0001	-0.0001 (0.0009) *(0.0010)* 0.0003	-0.0001 (0.0010) *(0.0011)* 0.0000			

$AGE_{i,t-1}$	(0.0004) *(0.0005)*	(0.0004) *(0.0006)*	(0.0004) *(0.0005)*	(0.0004) *(0.0005)*	(0.0004) *(0.0006)*	(0.0004) *(0.0005)*	(0.0004) *(0.0005)*	(0.0005) *(0.0007)*	(0.0005) *(0.0006)*			
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	0.0001 (0.0003) *(0.0003)* 0.0001 (0.0003) *(0.0003)*	0.0005 (0.0006) *(0.0006)* -0.0006 (0.0007) *(0.0007)*	0.0006 (0.0007) *(0.0008)* -0.0005 (0.0009) *(0.0009)*									
$UNEM_{it}$ $UNEM_{i,t-1}$				-0.0315 (0.0300) *(0.0390)* 0.0029 (0.0273) *(0.0199)*	-0.0064 (0.0535) *(0.0579)* 0.0098 (0.0365) *(0.0384)*	0.0270 (0.0704) *(0.0690)* 0.0384 (0.0581) *(0.0692)*						
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$							0.0105 (0.0233) *(0.0253)* 0.0142 (0.0194) *(0.0130)*	0.1133 (0.0504)** *(0.0557)* ** -0.0228 (0.0311) *(0.0314)*	0.0700 (0.0610) *(0.0585)* 0.0027 (0.0541) *(0.0572)*			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				0.0002 (0.0003) *(0.0003)* 0.0002 (0.0003) *(0.0002)*	0.0008 (0.0005) *(0.0006)* -0.0006 (0.0005) *(0.0005)*	0.0006 (0.0006) *(0.0005)* -0.0005 (0.0007) *(0.0007)*	0.0002 (0.0003) *(0.0003)* 0.0003 (0.0003) *(0.0002)*	0.0012 (0.0006)** *(0.0006)* ** -0.0012 (0.0006)** *(0.0006)* **	0.0010 (0.0007) *(0.0006)* -0.0010 (0.0007) *(0.0010)*			
OBS.	285			285			285					
SARGAN TEST (p-value)	20.97 (0.0128)	49.85 (0.1617)	26.98 (0.3567)	21.07 (0.0123)	63.15 (0.0843)	41.49 (0.0624)	20.53 (0.0149)	47.18 (0.5473)	34.04 (0.2377)			
AR(1) TEST (p-value)	-1.77 (0.0766) *-1.73* *(0.0833)*	-3.31 (0.0009) *-1.98* *(0.0478)*	-2.06 (0.0397) *-1.72* *(0.0860)*	-1.67 (0.0947) *-1.66* *(0.0975)*	-3.66 (0.0003) *-2.32* *(0.0202)*	-2.09 (0.0366) *-2.09* *(0.0362)*	-1.76 (0.0790) *-1.78* *(0.0744)*	-4.44 (0.0000) *-2.42* *(0.0154)*	-2.58 (0.0099) *-1.61* *(0.1064)*			
AR(2) TEST (p-value)	-0.82 (0.4142) *-1.09* *(0.2747)*	-0.70 (0.4865) *-0.74* *(0.4610)*	-1.10 (0.2711) *-1.04* *(0.2987)*	-0.71 (0.4751) *-0.97* *(0.3336)*	-0.38 (0.7042) *-0.41* *(0.6818)*	-0.72 (0.4702) *-0.72* *(0.4723)*	-0.76 (0.4494) *-1.04* *(0.3000)*	0.06 (0.9557) *0.06* *(0.9510)*	-0.06 (0.9561) *-0.05* *(0.9629)*			

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. 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.

Appendix A6.26: Short Run GMM: Dependent Variable is AGE1 and Independent Variables are NMN and NGE1

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous
$AGE1_{i,t-1}$	0.5747 (0.1913)*** (0.2167)***	0.4429 (0.1589)*** (0.2309)*	0.5498 (0.2030)*** (0.2309)**	0.3343 (0.1929)* (0.1897)*	0.0647 (0.1407) (0.1713)	0.0269 (0.1695) (0.1582)	0.3019 (0.1836) (0.1961)	0.0449 (0.1385) (0.1579)	0.0212 (0.1677) (0.1534)	0.3017 (0.1825)* (0.1946)	0.0295 (0.1355) (0.1399)	0.0104 (0.1705) (0.1708)
AMN_{it} $AMN_{i,t-1}$	0.0054 (0.0008)*** (0.0016)*** -0.0070 (0.0016)*** (0.0018)***	0.0030 (0.0013)** (0.0019) -0.0031 (0.0023) (0.0023)	0.0008 (0.0018) (0.0021) -0.0009 (0.0029) (0.0032)	0.0059 (0.0008)*** (0.0016)*** -0.0053 (0.0016)*** (0.0015)***	0.0026 (0.0013)* (0.0019) -0.0018 (0.0017) (0.0018)	0.0015 (0.0017) (0.0022) -0.0012 (0.0020) (0.0021)	0.0059 (0.0008)*** (0.0015)*** -0.0051 (0.0015)*** (0.0015)***	0.0026 (0.0013)* (0.0018) -0.0015 (0.0017) (0.0018)	0.0016 (0.0017) (0.0021) -0.0010 (0.0020) (0.0021)	0.0059 (0.0008)*** (0.0015)*** -0.0050 (0.0015)*** (0.0015)***	0.0026 (0.0013)* (0.0017) -0.0022 (0.0017) (0.0018)	0.0013 (0.0018) (0.0018) -0.0019 (0.0020) (0.0020)
NMN_{it} $NMN_{i,t-1}$				0.0004 (0.0002) (0.0002) 0.0004 (0.0003) (0.0003)	0.0006 (0.0003)* (0.0005) 0.0001 (0.0004) (0.0005)	0.0006 (0.0003)* (0.0005) 0.0002 (0.0004) (0.0004)	0.0004 (0.0002)* (0.0002)* 0.0003 (0.0003) (0.0002)	0.0006 (0.0003)** (0.0005) 0.0000 (0.0004) (0.0005)	0.0006 (0.0003)* (0.0005) 0.0001 (0.0004) (0.0004)	0.0005 (0.0002)** (0.0002)* 0.0004 (0.0003) (0.0002)	0.0006 (0.0003)** (0.0005) 0.0000 (0.0004) (0.0005)	0.0006 (0.0003) (0.0005) 0.0001 (0.0005) (0.0004)
$NGE1_{it}$ $NGE1_{i,t-1}$				-0.0008 (0.0074) (0.0052) 0.0110 (0.0077) (0.0086)	0.0359 (0.0186)* (0.0204)* 0.0318 (0.0157)** (0.0299)	0.0393 (0.0257) (0.0309) 0.0409 (0.0213)* (0.0273)	0.0001 (0.0074) (0.0057) 0.0114 (0.0077) (0.0085)	0.0349 (0.0184)* (0.0199)* 0.0340 (0.0152)** (0.0276)	0.0349 (0.0249) (0.0311) 0.0442 (0.0210)** (0.0259)*	-0.0011 (0.0075) (0.0060) 0.0105 (0.0078) (0.0082)	0.0460 (0.0159)*** (0.0229)** 0.0201 (0.0143) (0.0265)	0.0568 (0.0224)** (0.0317)* 0.0282 (0.0206) (0.0278)
AGE_{it} $AGE_{i,t-1}$							0.0008 (0.0006) (0.0006) -0.0003 (0.0004) (0.0005)	0.0010 (0.0006)* (0.0006)* -0.0004 (0.0004) (0.0005)	0.0008 (0.0006) (0.0007) -0.0004 (0.0004) (0.0005)	-0.0106 (0.0165) (0.0208) -0.0176 (0.0150) (0.0119)	0.0008 (0.0006) (0.0005) -0.0003 (0.0004) (0.0004)	0.0006 (0.0007) (0.0007) -0.0004 (0.0005) (0.0005)
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$										0.0008 (0.0006) (0.0006) -0.0002 (0.0004) (0.0004)	-0.0540 (0.0314)* (0.0459) 0.0075 (0.0268) (0.0254)	-0.0737 (0.0398)* (0.0490) -0.0180 (0.0478) (0.0397)
$ECACRA_{it}$ $ECACRA_{i,t-1}$												
$UNEM_{it}$ $UNEM_{i,t-1}$												
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$												

$ECACRF_{it}$ $ECACRF_{i,t-1}$												
OBS.	348			348			348			348		
SARGAN TEST (p-value)	24.97 (0.0030)	34.76 (0.0067)	20.59 (0.0814)	21.85 (0.0094)	49.97 (0.0294)	30.20 (0.0880)	21.53 (0.0105)	47.66 (0.0475)	30.36 (0.0851)	20.94 (0.0129)	50.49 (0.1471)	30.19 (0.2173)
AR(1) TEST (p-value)	-4.30 (0.0000) *-3.32* *(0.0009)*	-4.18 (0.0000) *-2.37* *(0.0180)*	-4.50 (0.0000) *-2.95* *(0.0031)*	-2.94 (0.0033) *-2.77* *(0.0057)*	-1.95 (0.0512) *-1.23* *(0.2189)*	-1.44 (0.1497) *-1.13* *(0.2572)*	-2.93 (0.0034) *-2.61* *(0.0090)*	-1.88 (0.0606) *-1.34* *(0.1792)*	-1.43 (0.1539) *-1.20* *(0.2304)*	-2.86 (0.0043) *-2.57* *(0.0103)*	-2.06 (0.0390) *-1.51* *(0.1310)*	-1.14 (0.2527) *-0.94* *(0.3482)*
AR(2) TEST (p-value)	0.36 (0.7205) *0.42* *(0.6780)*	0.07 (0.9443) *0.08* *(0.9387)*	0.44 (0.6601) *0.47* *(0.6368)*	-0.33 (0.7416) *-0.41* *(0.6815)*	-0.70 (0.4868) *-0.61* *(0.5400)*	-1.22 (0.2243) *-1.15* *(0.2501)*	-0.68 (0.4948) *-0.85* *(0.3929)*	-1.07 (0.2839) *-1.07* *(0.2863)*	-1.59 (0.1114) *-1.56* *(0.1187)*	-0.65 (0.5154) *-0.85* *(0.3962)*	-0.58 (0.5635) *-0.60* *(0.5501)*	-0.66 (0.5117) *-0.62* *(0.5329)*

	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} predetermine d	(c) x_{it} endogenous	(a) x_{it} strictly exogenous	(b) x_{it} predetermine d	(c) x_{it} endogenous			
$AGE1_{i,t-1}$	0.1816 (0.2021) *(0.2081)*	0.1435 (0.1265) *(0.1144)*	0.1333 (0.1471) *(0.1292)*	0.1578 (0.1990) *(0.2082)*	0.2002 (0.1284) *(0.1181)**	0.1059 (0.1465) *(0.1385)*	0.1854 (0.1995) (0.2106)	0.2392 (0.1253)* *(0.1079)***	0.1702 (0.1438) *(0.1337)*			
AMN_{it} $AMN_{i,t-1}$	0.0051 (0.0009)*** *(0.0015)**** -0.0042 (0.0016)*** *(0.0014)****	0.0019 (0.0013) *(0.0019)* -0.0023 (0.0018) *(0.0016)*	0.0012 (0.0018) *(0.0023)* -0.0012 (0.0022) *(0.0021)*	0.0052 (0.0009)*** *(0.0015)**** -0.0043 (0.0016)*** *(0.0016)****	0.0025 (0.0014)* *(0.0017)* -0.0020 (0.0019) *(0.0021)*	0.0026 (0.0019) *(0.0024)* -0.0029 (0.0022) *(0.0030)*	0.0052 (0.0009)*** *(0.0015)**** -0.0042 (0.0016)*** *(0.0015)****	0.0027 (0.0014)* *(0.0021)* -0.0025 (0.0019) *(0.0018)*	0.0022 (0.0020) *(0.0025)* -0.0036 (0.0023) *(0.0022)**			
NMN_{it} $NMN_{i,t-1}$	0.0006 (0.0003)** *(0.0003)*** 0.0002 (0.0003) *(0.0003)*	0.0007 (0.0004)* *(0.0005)* -0.0003 (0.0004) *(0.0005)*	0.0009 (0.0004)** *(0.0005)** -0.0002 (0.0005) *(0.0005)*	0.0007 (0.0003)** *(0.0003)*** 0.0002 (0.0003) *(0.0002)*	0.0006 (0.0004) *(0.0006)* -0.0001 (0.0004) *(0.0004)*	0.0008 (0.0004)* *(0.0006)* 0.0001 (0.0005) *(0.0005)*	0.0007 (0.0003)** *(0.0003)*** 0.0002 (0.0003) *(0.0003)*	0.0004 (0.0004) *(0.0004)* -0.0002 (0.0004) *(0.0005)*	0.0006 (0.0004) *(0.0005)* -0.0004 (0.0006) *(0.0006)*			
$NGE1_{it}$ $NGE1_{i,t-1}$	-0.0018 (0.0101) *(0.0078)* 0.0183 (0.0093)* *(0.0094)**	0.0403 (0.0219)* *(0.0265)* 0.0423 (0.0159)*** *(0.0215)***	0.0375 (0.0342) *(0.0437)* 0.0461 (0.0215)** *(0.0178)***	-0.0006 (0.0101) *(0.0073)* 0.0176 (0.0094)* *(0.0092)**	0.0251 (0.0211) *(0.0234)* 0.0373 (0.0155)** *(0.0190)**	0.0464 (0.0281)* *(0.0329)* 0.0416 (0.0202)** *(0.0149)****	-0.0012 (0.0101) *(0.0075)* 0.0179 (0.0094)* *(0.0098)**	0.0138 (0.0219) *(0.0209)* 0.0339 (0.0157)** *(0.0185)**	0.0327 (0.0277) *(0.0299)* 0.0368 (0.0213)* *(0.0183)***			
AGE_{it}	0.0001 (0.0003) *(0.0002)* 0.0000	0.0010 (0.0007) *(0.0008)* -0.0005	0.0009 (0.0008) *(0.0009)* -0.0005	0.0002 (0.0003) *(0.0002)* 0.0002	0.0008 (0.0008) *(0.0009)* -0.0004	0.0009 (0.0008) *(0.0009)* -0.0006	0.0007 (0.0007) *(0.0007)* -0.0002	0.0000 (0.0009) *(0.0009)* -0.0001	0.0000 (0.0009) *(0.0009)* -0.0001			

$AGE_{i,t-1}$	(0.0003) _(0.0003)_	(0.0005) _(0.0005)_	(0.0005) _(0.0006)_	(0.0003) _(0.0002)_	(0.0005) _(0.0005)_	(0.0005) _(0.0005)_	(0.0004) _(0.0005)_	(0.0005) _(0.0005)_	(0.0005) _(0.0006)_			
$LFSTOCK_{it}$ $LFSTOCK_{i,t-1}$												
$ECACRA_{it}$ $ECACRA_{i,t-1}$	0.0009 (0.0007) _(0.0007)_ -0.0002 (0.0004) _(0.0005)_	0.0003 (0.0005) _(0.0005)_ -0.0003 (0.0007) _(0.0007)_	0.0001 (0.0007) _(0.0008)_ 0.0000 (0.0009) _(0.0010)_									
$UNEM_{it}$ $UNEM_{i,t-1}$				0.0009 (0.0007) _(0.0007)_ -0.0002 (0.0004) _(0.0005)_	-0.0106 (0.0511) _(0.0811)_ 0.0197 (0.0371) _(0.0385)_	-0.0355 (0.0678) _(0.0870)_ 0.0500 (0.0567) _(0.0719)_						
$INACTIVE_{it}$ $INACTIVE_{i,t-1}$							0.0178 (0.0229) _(0.0288)_ 0.0160 (0.0195) _(0.0130)_	0.0795 (0.0444)* _(0.0513)_ -0.0075 (0.0300) _(0.0276)_	0.1118 (0.0558)** _(0.0668)_* -0.0223 (0.0550) _(0.0664)_			
$ECACRF_{it}$ $ECACRF_{i,t-1}$				-0.0252 (0.0300) _(0.0364)_ 0.0013 (0.0276) _(0.0197)_	0.0009 (0.0005)* _(0.0005)_* -0.0008 (0.0006) _(0.0007)_	0.0006 (0.0006) _(0.0005)_ 0.0001 (0.0008) _(0.0006)_	0.0002 (0.0003) _(0.0003)_ 0.0002 (0.0003) _(0.0002)_	0.0012 (0.0005)** _(0.0006)_** -0.0014 (0.0005)** _(0.0007)_*	0.0007 (0.0007) _(0.0007)_ -0.0008 (0.0007) _(0.0009)_			
OBS.	285			285			285					
SARGAN TEST (p-value)	24.27 (0.0039)	50.88 (0.1387)	28.07 (0.3045)	24.17 (0.0040)	63.36 (0.0815)	42.29 (0.0529)	23.30 (0.0056)	56.14 (0.2249)	32.63 (0.2930)			
AR(1) TEST (p-value)	-2.13 (0.0334) _-1.98_ _(0.0478)_	-3.07 (0.0022) _-2.17_ _(0.0301)_	-2.65 (0.0080) _-2.19_ _(0.0285)_	-2.01 (0.0442) _-1.87_ _(0.0609)_	-4.05 (0.0001) _-2.84_ _(0.0045)_	-2.51 (0.0121) _-2.47_ _(0.0133)_	-2.06 (0.0391) _-1.97_ _(0.0493)_	-4.63 (0.0000) _-2.79_ _(0.0053)_	-2.95 (0.0032) _-1.91_ _(0.0561)_			
AR(2) TEST (p-value)	-0.34 (0.7368) _-0.49_ _(0.6274)_	-0.24 (0.8136) _-0.26_ _(0.7948)_	-0.42 (0.6723) _-0.44_ _(0.6620)_	-0.34 (0.7362) _-0.49_ _(0.6269)_	0.33 (0.7421) _0.36_ _(0.7210)_	-0.12 (0.9079) _-0.12_ _(0.9064)_	-0.26 (0.7911) _-0.38_ _(0.7018)_	0.62 (0.5383) _0.66_ _(0.5082)_	0.61 (0.5420) _0.53_ _(0.5970)_			

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator. 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.

7 Chapter Seven. Regional Economic Growth and Income and Educational Inequality

7.1 Introduction

The linkage between inequality and growth is far from being well understood, especially in its regional context. When looking at the effects of income and educational inequality on regional economic growth, we are primarily interested in the ways in which distribution can affect aggregate output and growth through its impact on different channels. The impact of inequality on growth remains controversial and decades of economic, sociological and political studies offer evidence that the inequality-growth relationship is, indeed, complex (Galor, 2000; Galor and Moav, 2004). There is a range of theoretical and empirical evidence suggesting that inequality can actually be good for growth (i.e. Mirrlees, 1971; Rebelo, 1991), while other studies support the idea that inequality may harm growth (i.e. Perotti, 1996; Easterly, 2001).

The analysis performed here aims to shed light on the inequality-growth relationship. This chapter addresses the main research question of this thesis. Do income and educational inequalities matter for growth? To what extent are inequalities associated with growth? Given that income inequalities are associated with educational inequalities and they are affected by common factors (see Chapter 6), this chapter also explores whether those factors affect regional economic growth either directly or indirectly through their impact on inequalities. Although income and educational inequalities are highly correlated, this chapter attempts to synthesise the impact of inequalities on growth, comparing the magnitude and significance of their coefficients. The methodology is based on the estimation of static regression models.

The aim of this chapter is the focal point of this research. It examines how microeconomic changes in income and educational distribution affect the evolution of regional economic growth in the EU. As has been stated previously, microeconomic changes in income and in human capital endowments are measured in terms of average measures and inequality. This chapter contributes to two different strands within the field of economic growth: the relationship of income per capita, educational attainment and growth (the first strand); and inequality and growth (the second strand). To this end, it examines which strand outweighs the other. This is a significant omission in the literature to date.

The remainder of this chapter proceeds as follows. In the next section, I present the theoretical background on the impact of the labour- and physical capital-related variables and the role of urbanisation, geography and institutions . Section 7.3 illustrates the combined impact of income and educational inequality on growth, while Section 7.4 explores causality issues. The last section discusses the conclusions, the implications and the limitations of the results. It also offers some policy recommendations.

7.2 The Determinants of Growth

This section discusses the theoretical background with regard to the determinants of growth. The growth literature presented here is not meant to be exhaustive, but rather it highlights those areas of thought and empirical work relevant to an investigation of the impact of the labour- and physical capital-related variables and of some time-invariant variables. The first subsection considers the economic impact of population ageing, access to work, unemployment and inactivity. The second provides an overview on the possible impacts of transport infrastructures, and more specifically, of road and rail infrastructures, on growth. The last subsection discusses the theoretical background on the impact of urbanisation, geography and institutions on growth.

7.2.1 Labour-related Variables

7.2.1.1 Population Ageing

Population ageing has a significant impact not only on income and human capital distribution, but also on regional economic growth. A number of theoretical and empirical arguments have been constructed in order to assess the linkage between population ageing and economic growth through different channels such as an individuals' natural capacity, incentives to produce, technical progress, tax structure, savings and government policy responses.

On the one hand, it would seem plausible to assume that the relationship between population ageing and growth should be negative. Older workers are, on average, less productive than younger ones for several reasons (Tang and MacLeod, 2006). First, younger and older workers differ in their levels of technology adoption, as the former are the primary adopters and beneficiaries of new the technologies that are most probably more productive than old technologies, while the latter tend to be more set in their ways and to be less willing to learn new ways of doing things, partly due to a natural decline in their capacity (Galenson and Weinberg, 2000, 2001). Second, younger and older workers tend to differ in work effort, as younger workers work more hours and are able to concentrate more on the job, they are healthier on average and thus take fewer days in sick leave than older workers (Cheal, 2000). Since productivity declines as a worker gets closer to retirement (Diamond, 1986; Oster and Hamermesh, 1998; Bhattacharya and Russell, 2001), population ageing has a negative impact on regional economic growth. Nevertheless, Disney (1996) argues that the relationship between an ageing labour force and productivity is unclear. Hence, differences in technology adoption and work effort may lead to different productive capacities across different age groups of the workforce.

A somewhat different view has been built on the assumption that retired people tend to spend their savings, decreasing capital investment, while working people save for their retirement. Therefore, if a longer life span increases the ratio of retired people to working people, it reduces the aggregate saving rate, which decelerates economic growth (Futagami and Nakajima, 2001).

On the other hand, the relationship between population ageing and economic growth may be positive. Changes in the demographic composition of a regional economy affect its production structure. Descriptive statistical analysis has shown that population ageing has increased between 1996 and 2000. The labour force has declined because of the rapid population ageing. However, a declining labour force does not necessarily reduce potential growth as production is more capital-intensive. New technology is embodied in new machines and investment is induced by technical progress, which is the ultimate source of growth (Hicks, 1977). Capital and technical progress are much more important than labour in determining growth (Yoshikawa, 2000). Additionally, population ageing is beneficial for economic growth because young people invest more capital in preparation for their longer life-spans (Pecchenino and Pollard, 1997).

It is known that the increase in population ageing is due to the declining birth rate and increased life expectancy. Some studies, such as those by de la Croix and Licandro (1999), Fuster (1999), Cipriani (2000), and Boucekkine et al. (2002) posit an inverted U-shaped relationship between life expectancy and growth. In economies in which life expectancy is sufficiently low, an increase in life expectancy motivates agents to save more for their old-age, increasing the aggregate saving rate, and thus enhancing the growth rate of the economy; while in economies in which life expectancy is sufficiently high, a rise in life expectancy increases the healthcare cost burden to young agents,[91] reducing the aggregate saving rate, and thus lowering the growth rate (Tabata, 2005: 474).

Demographic changes may also have significant economic consequences, depending on the position taken with regard to important policy measures and challenges. Policies on fertility and pensions are likely to affect the ageing-growth relationship. If, for instance, the state pension age were to increase, it is likely to alter regional productivity and growth. An ageing population shifts the underlying distribution of preferences in a way that results in stronger demands for unemployment benefits, health insurance, pensions and public expenditure in general, which reduce potential growth (Boix, 2001). Futagami and Nakajima (2001) examine the effects of a policy of postponing the retirement age and suggest that such a policy would slow growth. Moreover, a policy aimed at attracting young immigrant workers from abroad would serve to reduce regional population ageing, which in turn affects growth either positively or negatively. Consequently, social policy reform is a subject that matters greatly for both economic growth and age distribution.

To summarise, population ageing has an effect on economic growth, depending on the adjustment of factor inputs (labour, capital, technical progress) and on government policy responses (policies on fertility and pensions).

7.2.1.2 Access to Work

Differentials in growth rates may arise from differences in workforce participation, particularly between men and women. The effect of access to work on regional economic growth seems to be clear-cut. Access to work usually stimulates growth. First, higher participation in labour market is argued to contribute to a competitive economic environment, promoting allocative efficiency (i.e. sectoral factor reallocation), and thus enhancing economic growth (Azzoni and Silveira-Neto, 2005). Second, higher labour force participation implies more work-related education and training, which are positively associated with wage and income growth (Lynch, 1992; Bartel, 1995; Parent,

[91] The elderly need much more healthcare, including nursing care and other social services, and the medical care required by older people often involves relatively expensive technology and hospitalisation, increasing the healthcare cost of the economy (Tabata, 2005).

1999). Third, work access differs by gender. Women and men, on average, occupy different class positions, with women more likely to be poor and less-educated relative to the position of men, implying gender wage and social differentials. Women not only hold the majority of low-income jobs, but also have less continuous employment than men and do not receive the same job rewards. Women are often placed in jobs where less training is provided due to their lower labour force attachment (Barron et al., 1993; Royalty, 1996). These differentials may be a stimulus to export expansion (Seguino, 2000). Export earnings may provide the resources to purchase sophisticated technologies, which permit economies of scale and specialisation and enhance economic growth. However, low female wages that stimulate exports may not be sufficient to promote growth, because the labour force should be able to competently adopt new technologies. State policies and institutions that promote learning, to enable workers to integrate new imported technologies, are also required (Amsden, 1989). Therefore, gender wage inequality could have a positive effect on growth via the effect on investment under certain structural economic and political conditions. In other words, greater access to work for women is likely to promote regional economic growth due to their low wage levels. If, on the other hand, economic inefficiencies arise from persisting gender differentials in the labour market (Tzannatos, 1999), greater female access to work may stimulate growth because higher employment means a greater level of inputs and that firms can produce more.

Nevertheless, the effect of work access on regional economic growth may be negative via the effect on income distribution. More specifically, greater work access is likely to reduce income inequality (see Chapter 6), which may reduce economic growth. Additionally, the causal link between regional growth and work access might be negative. In countries with low per capita income and growth, most people remain in the labour force until a very advanced age or until they are unable to continue working. Hence, as income and growth increase, the structural changes in the economy (i.e. a decline in agricultural employment) imply a lower labour force participation (Clark et al., 1999). Finally, policies are likely to affect the relationship between growth and work access. For example, higher labour regulation is associated with lower labour force participation and higher unemployment, especially among the young (Botero et al., 2004).

7.2.1.3 Unemployment and Inactivity

The relationship between unemployment and growth is not clear-cut. One of the major difficulties is that multiple linkages exist between these two variables, and many common factors exert an influence upon them (Muscatelli and Tirelli, 2001).

Four different views have emerged on the relationship between unemployment and growth. The first view is that the rate of unemployment is independent of the rate of economic growth (Phelps, 1968). Thus, research on growth and on unemployment should be carried out independently, as is the case with the empirical study by Layard et al. (1991). The second strand of theories (i.e. Stadler, 1990; Muscatelli and Tirelli, 2001) is based on the notion that periods of low economic activity and high unemployment have an adverse effect on growth. The higher the unemployment rate, the greater the skill losses, the greater the unexploited opportunities for learning-by-doing and the greater the inefficiencies in the production of human capital, and thus the lower the growth rate. The third view is that periods of high growth tend to be periods of high unemployment (Hall, 1991; Caballero and Hammour, 1994). High levels of economic inactivity and unemployment stimulate efficiency gains by causing less efficient firms to exit and encourage firms to adopt reorganising investments and innovative activities. This leads to faster economic growth, only if the entry rates of new and more efficient firms and the reorganising investment rates of existing firms are not too low during periods of recession. Hence, recessions may also stimulate regional economic growth.

The last strand of the literature highlights the causal links running from economic growth to unemployment. The model developed by Pissarides (2000), and based on neoclassical growth theory, shows that a growth in labour productivity increases the value of hiring an employee for firms. In other words, an increase in growth raises the capitalised returns from creating jobs, inducing a faster exit rate from unemployment. Therefore, as a result of higher growth, firms increase the number of vacancies posted and unemployment declines. More economic growth requires more R&D which, in turn, requires more labour and leads to more employment. This negative effect of growth on unemployment is known as the capitalisation effect. The model developed by Aghion and Howitt (1994), based on the endogenous growth theory (Aghion and Howitt, 1992), compares the two competing effects of growth on unemployment. The first is the capitalisation effect and the second is the creative destruction effect. According to the latter effect, an increase in economic growth may reduce the duration of a job match, raising the level of unemployment both directly, by raising the lay-off rate (job-separation rate), and indirectly, by discouraging the creation of job vacancies and hence reducing the job-finding rate. Increased growth reduces the life expectancy of a firm and thus increases unemployment. In Aghion and Howitt's model (1994), growth results from the introduction of innovative production systems and of new technologies that require labour reallocation for their implementation. The balance between the capitalisation and the creative destruction effect depends on the costs of implementation, which vary widely across firms, industries and sectors (Mortensen and Pissarides, 1994).

Many other factors are likely to influence the causal relationship between unemployment and growth, such as saving behaviour (Bean and Pissarides, 1993), trade unions (Bean and Crafts, 1995), labour market policy (Mortensen, 2005) and immigration (Bencivenga and Smith, 1997). For instance, if people who are not economically active leave regions with low levels of GDP per capita and join those with high levels, GDP per capita and growth will increase in the former and decrease in the latter (Fagerberg et al., 1997). However, if some people are more productive and innovative than others because, for example, they are better educated, growth might decrease (Fagerberg et al., 1997).

The empirical research on the relationship between unemployment and growth has yielded mixed results. Bean and Pissarides (1993) find no correlation between unemployment and productivity growth across OECD economies. Muscatelli and Tirelli (2001) and Mauro and Carmeci (2003) provide evidence of a negative unemployment-growth relationship, while Caballero (1993) and Hoon and Phelps (1997) find a positive relationship. Therefore, there is no consensus regarding the sign of the correlation between unemployment and growth.

7.2.2 Physical Capital-related Variables: Transport Infrastructures

The impact of transport infrastructures on economic growth is different for motorways and railways and is a highly complex issue involving aspects of public-good provision, the generation of externalities, political decision-making and long time periods (McCann and Shefer, 2004).

Most studies have accepted the position that transport infrastructures contribute positively to economic growth. The pioneering studies of Aschauer (1989a, 1989b) concluded that public capital (including transport infrastructures) was a factor of enormous importance in explaining the evolution of economic growth in the United States. Later studies (Duffydeno and Eberts, 1991; Banister and Berechman, 2000) provided additional evidence for the results obtained by Aschauer. The theoretical background on the positive relationship between transport infrastructures and economic growth is multifarious. First, the net benefits associated with the public transport infrastructure are related to increases in the net local income, which stem from either private investments due to the reductions in transport costs and travel times or positive externalities as the income of the non-users of the infrastructure may increase due to increases in local demand on the part of the infrastructure users (McCann and Shefer, 2004). Second, investments in transportation change the relative accessibility of a region. An increase in the level of connectivity implies a greater ability on the part of local firms to develop profitable market relationships with firms and consumers either within or between regions. In other words, a high quality transport infrastructure creates opportunities for interaction among firms and customers. Firms that are located in areas with a better infrastructure will be more integrated into the market system and more exposed to competition and, thus, under more pressure to improve productivity (Deichmann et al., 2004). Greater choice, innovation and intellectual opportunities for agents imply the development of inter-regional and intra-regional linkages, and thus higher growth (Vickerman 1991). When the road and rail infrastructure improves the relative accessibility of a region, it can provide for an increased rate of return on investments relative to other competing locations (McCann and Shefer, 2004: 181). Additional mobile resources (either capital or labour) from outside the region may be attracted to the area with the new infrastructure. This immigration of factors contributes to regional growth. Based on this evidence, where transport infrastructure facilities are developed, it is easier for entrepreneurs to adopt new technologies and, consequently, this generates technical progress and regional economic growth (Demurger, 2001). Third, poor resource endowments may lead to limited access to educational and socioeconomic opportunities. Transport infrastructures offset some of the inherent disadvantages of lagging regions, because they connect remote regions to urban areas (Henderson et al., 2001). Fourth, transport infrastructures reinforce the cumulative causation process. Firms produce more efficiently and workers enjoy higher levels of welfare by being linked to large markets through a good transport infrastructure network. The large markets are, in turn, those where more firms and workers are located. Fifth, a good infrastructure network across regions might imply efficiency in the transportation of inputs (labour and capital) as well as potential increases in their price, and thus a higher growth rate. Transport facilities for both passengers and freight are usually critical to the competitiveness and prosperity of a region (European Commission, 1999). Without a good infrastructure network, problems of both inefficiency and competitiveness may impede economic development (Demurger, 2001). Therefore, infrastructure can contribute to growth, either directly as a measurable final product, or indirectly as an intermediate input, because infrastructure enhances the productivity of all other inputs in producing output (Wang, 2002) and it generates positive externalities. In other words, the first impact comes from the construction expenditure, while the second comes from the costs and revenues associated with its operation (Puga, 2002).

The results of some studies, either at national or at regional levels, seem to contradict the widely accepted hypothesis that investment in the transport infrastructure always favours high rates of economic growth (Holtz-Eakin, 1994; Holtz-Eakin and Lovely, 1996). However, while a transport infrastructure may encourage development in under-developed regions, its construction alone will not be enough to bring about any desired economic changes (McCann and Shefer, 2004: 179). Other factors such as the resource endowments of the region, the economic climate in the region, the prices of the input factors of production, government policies and underlying infrastructure tend to determine the economic viability of a region, far more than its transport infrastructures (Vickerman, 1991; McCann and Shefer, 2004). Complementary actions and policies need to be taken to ensure that lagging regions are in a position to profit from the opportunities created by improvements in road and rail transport (European Commission, 1999). Additionally, the benefits of a good transport infrastructure are not necessarily unlimited. If infrastructure investments increase the rate of growth, this does not imply that further investments will increase growth even more (Puga, 2002). Some of the more central regions of the EU arguably face constraints on future economic development, despite high levels of transport infrastructure endowment, because of the inability of the structure in place to cope with further economic growth (European Commission, 1999). The nature of road infrastructure tends to mean that there are capacity limits, beyond which negative externalities (i.e. congestion costs) start to dominate. Productivity will decline as congestion exceeds a certain threshold level (Glaeser and Kohlhase, 2004). Hence congestion on urban roads may have a negative impact on productivity and thus lead to a negative growth rate. The existing transport infrastructure may become obsolete because of high spatial movements of the population and business activity or a change in technology (McCann and Shefer, 2004).

According to Puga (2002: 396), a better connection between two regions with different economic development levels not only gives firms in a remote region better access to the inputs and markets of more developed regions, but also makes it easier for firms in richer regions to supply poorer regions at a distance, and can thus harm the industrialisation prospects of less developed areas.

A network of transport infrastructures may indirectly influence regional economic growth either positively or negatively, through other public infrastructures such as the public buildings for education and hospitals. A public infrastructure investment in a region has effects not only on that region, but also on other regions connected by a network (Hulten, 1991). Regional spillovers can exist insofar as the network can generate positive or negative external effects beyond the regions where infrastructures are located.

Reverse causation in growth-infrastructure relationship might matter. Not only may public infrastructure influence regional economic growth, but growth is also likely to affect the expansion of public investments. The existing empirical evidence (Duffy-Deno and Eberts, 1991; Holtz-Eakin, 1994; Looney, 1997) remains ambiguous as to whether a positive correlation indicates that the public infrastructure raises private output or a rise in private output raises the demand for infrastructure (Wang, 2002). It is not clear in which direction the causal relationship runs. The nature of the causal link is still a subject of debate (European Commission, 1999). Looney (1997), for instance, found that public facilities expanded largely in response to the needs of the private sector.

There are many characteristics that distinguish road from rail infrastructure. Those characteristics may distinguish the impact of road infrastructure on growth from that of a rail network. First of all, a motorway is a light transport infrastructure, while railway is a heavy one. According to Puga (2002), the road infrastructure is likely to have a more substantial effect on the spatial allocation of production, and hence on regional inequalities. Lynde and Richmond (1992) have argued that public capital can play an important complementary role in the productivity of the regional private sector. The complementary role of road infrastructures in productivity is more significant than the role of rail infrastructure, because the services of the former are mostly freely distributed to private producers. The sunk infrastructure cost of railways (especially high-speed rail) is higher than the cost of roads. The value of the transportation infrastructure can vary significantly, not only among different forms of transport, but also from sector to sector and firm to firm (McCann and Shefer, 2004). For example, high-speed rail lines are generally not suitable for the transportation of goods, and are thus unlikely to have much effect on the location of industry (Puga, 2002).

According to the European Commission (1999), the simplest measure of infrastructure is the physical scale of provision in relation to the potential use. Physical measures of the existing transport stock are used, as in Biehl's (1986) analysis. More specifically, road stock $(ROAD)$ is measured as the average (between 1995 and 2000) of the length of road-motorways per square kilometre, while rail capital $(RAIL)$ is measured as the average (between 1995 and 2000) of the length of railways per square kilometer. Both variables are assumed to be fixed and are extracted from the Eurostat's dataset. However, since the transport infrastructure of 1995–2000 had been constructed over a great many years, it may reflect lagged requirements and patterns of development rather than current and prospective ones (European Commission, 1999).

The physical scale measurement does not give a clear picture of infrastructure stock, because it is extremely difficult to approach an estimation of the qualitative characteristics of the infrastructure capacity (Rovolis and Spence, 2002: 394). Questions related to infrastructure measurements remain open to analysis in greater depth (Haughwout, 1998; European Commission, 1999; Haughwout, 2002).[92] Nevertheless, neither the indicators of scale nor of quality can convey how suitable the existing transport endowment in any region is to its regional development needs (European Commission, 1999: 122). Therefore, the indicators devised need to be interpreted with caution.

7.2.2.1 ***Road Infrastructure***

Most of the passenger and freight traffic in the EU travels by road. In 1996, for example, nearly 75 per cent of freight movements and more than 85 per cent of passenger movements were made by car (European Commission, 1999). A good road network is not only beneficial in itself, but it is also important to ensure effective use of other forms of transport (European Commission, 1999). Figure 7.1 shows the spatial distribution of road infrastructure $(ROAD)$. The economically stronger regions in the

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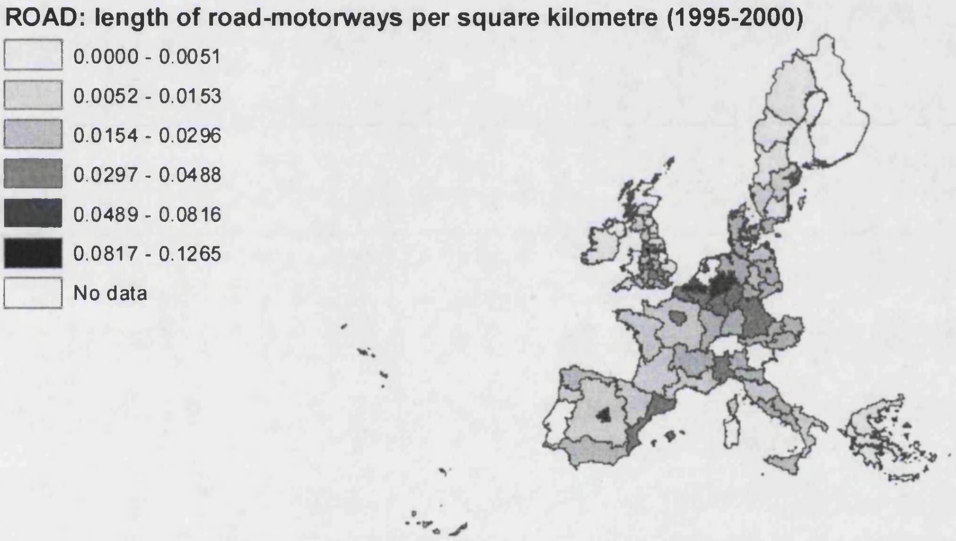
[92] Indicators of quality are more tricky to define. For the rail network, the extent of electrification and the number of separate tracks, which affect both the speed of the service and its carrying capacity, can be used to give a reasonable indication of quality (European Commission, 1999: 122).

EU, with higher levels of income and human capital, such as the city-regions, are generally better endowed than lagging and peripheral regions. The road infrastructure in Région Bruxelles-capitale, Vlaams Gewest, Bremen, Hamburg, Nordrhein-Westfalen, Comunidad de Madrid, Greater Manchester and the West Midlands is the densest. The road network in Belgium, Luxemburg and Germany is over twice as extensive as the EU average. By contrast, the network is much less extensive in Greece, Ireland, Scotland and northern Sweden. Roads tend to be concentrated not only in the more central areas with higher levels of economic activity, but also in the more peripheral areas like in the Spanish Este and Sur. To sum up, differences in road infrastructure are recognised as probably contributing significantly to variations in regional competitiveness and economic growth.

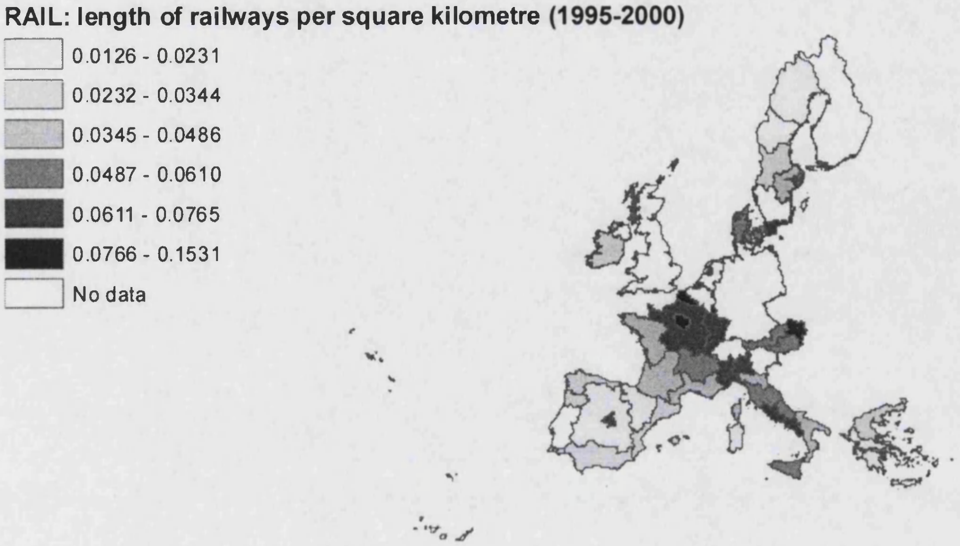
Figure 7.1: Spatial Distribution of the Road Infrastructure



7.2.2.2 Rail Infrastructure

Figure 7.2 shows the geographical distribution of the rail infrastructure (*RAIL*). The rail network in Île de France, Nord-Pas-de-Calais, Luxemburg and Ostösterreich is the most extensive in the EU, while it is much less extensive in Greece, Ireland, Scotland and northern Sweden (in Mellersta Norrland and Övre Norrland). The disparities in economic development are closely linked to geographical location and accessibility through a rail network, in the sense that the more peripheral and the less accessible the region, the lower its economic development. Finally, the rail network is much more extensive in large urban areas like Île de France.

Figure 7.2: Spatial Distribution of the Rail Infrastructure



7.2.3 Other Variables

One recurring theme in the literature on economic growth has been the topic of urbanisation, geography and institutions. One of the major difficulties is that multiple social, economic and political linkages exist between inequality and growth, and urbanisation, geography and institutions all exert an influence upon them. The empirical evidence in this area has been very thin.

7.2.3.1 Urbanisation

The role played by urbanisation (or economic agglomeration at the city level) in economic growth has been emphasised by urban economists (Henderson, 1988; Fujita and Thisse, 2002), development economists (Williamson, 1988), growth economists (Lucas, 1988) and economic historians (Hohenberg and Lees, 1985), among others. The main conclusion of this vast literature is, without a doubt, that growth and urbanisation are mutually self-reinforcing processes.

First of all, agglomeration in one region is likely to spur economic growth because it reduces the costs of innovation, infrastructure, information and transactions in that region through technological and pecuniary externalities.[93] This trend is evinced most

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[93] The former '*deal with the effects of nonmarket interactions that are realised through processes directly affecting the utility of an individual*', while the latter '*are by-products of market interactions*' and '*arise from imperfect competition*' (Fujita and Thisse, 2002: 8). Pecuniary externalities in Europe are determined by the intensity of returns to scale, market power and factor mobility (Fujita and Thisse, 2002: 9).

especially in the writings of the new growth and NEG theorists. Improvements in transport and communications processes, for instance, tend to reinforce the clustering of economic activity by widening the market range of any given centre and by helping to spark off new rounds of specialisation in established urban areas (Scott and Storper, 2003: 582). Cities also allow goods, ideas and people to come together for the purposes of exchange and production (Polese, 2005). This allows regions to reap the gains of trade and specialisation, increasing economic development. Cities, moreover, foster and facilitate flows of local knowledge, ideas and innovations, the creation of dense social networks and the production of behavioural and cultural change. In cities, people have face-to-face contact, which is a fundamental prerequisite of tacit knowledge spillovers. Interaction between people promotes innovation, continually pushing up productivity and growth (Jacobs, 1970). Although the advent of new information and communication technologies have enormously increased the quantity, complexity and variety of the information and knowledge generated, face-to-face contact complements rather than substitutes for each other form of contact, such as an e-mail contact (Leamer and Storper, 2001; McCann and Shefer, 2005).

Urbanisation is also likely to spur economic growth when its economic benefits outweigh its costs. On the one hand, the economic benefits of urbanisation arise due to the presence of knowledge spillovers among firms in an industry (Marshall, 1890), a buildup of knowledge and ideas associated with historical diversity (Jacobs, 1970), the local competition of an industry (Porter, 1989) and the lower infrastructure, information, transaction, training and recruitment costs (Polese, 2005). However, people may move to cities for reasons unrelated to their economic performance, for example, for the schools and local amenities. City life produces behavioural and cultural change such as changes in family structures and in religious beliefs. On the other hand, the costs of urbanisation arise due to the commuting expenditures within cities, the substantial pollution and the pervasive traffic congestion (Bertinelli and Black, 2004). The economic costs also arise from the pressure posed by geographic concentration on urban factor markets that bids up prices and from dispersed demand (Martin and Ottaviano, 2001).

Therefore, cities act as locations where technological, economic and social innovations are developed (Bräuninger and Niebuhr, 2005), enhancing the economic chances and opportunities of working people. Face-to-face interaction and 'tacit knowledge' promote innovation, productivity and economic development. Additionally, wages in cities are expected to be higher than in rural areas due to home market effects.

Nevertheless, reverse causation in the positive growth-urbanisation relationship is a subject of debate. Economic growth is likely to foster agglomeration, because as the sector at the origin of innovation expands, new firms tend to locate close to that sector (Martin and Ottaviano, 2001). The gains for a particular firm of being located in an urban area are scale economies due to greater market size, flexible and rapid input relationships and the presence of a large and diversified labour pool. The continuing agglomeration of human capital produces increasing returns to firms. The agglomeration of talented and educated individuals in specific areas encourages firms (i.e. research centres) to locate in those areas, and vice versa. According to the NEG context, the positive relationship indicates that the centripetal forces (i.e. knowledge spillovers and increasing returns to scale) are strong enough to offset the centrifugal forces (i.e. congestion and transportation costs).

A negative relationship between urbanisation and economic growth is likely to show that the centrifugal forces outweigh the centripetal ones. This relationship may highlight the rising costs of urban concentration due to pervasive traffic congestion, substantial pollution, escalating land prices, crime and family breakdown (Scott and Storper, 2003). For instance, the resource cost of transportation is likely to prevent a city from growing unboundedly (Palivos and Wang, 1996). Furthermore, public policy may shape the centripetal and centrifugal forces in various ways. Consequently, in many cases it is necessary to consider the relationship between public policies and economic growth (McCann and Shefer, 2004).

The city size also matters in the relationship between urbanisation and growth. Large cities depend more on 'urbanisation' economies,[94] while small cities depend more on 'localisation' economies (McCann and Shefer 2004).[95] Large cities, for instance, are locomotives of the national economies within which they are situated, in that they are the sites of dense masses of interrelated economic activities (Scott and Storper, 2003: 581). Large cities also offer a wider selection and better quality of the producer services

[94] 'Urbanisation' economies refer to the gains derived from location in a large and diversified urban area (Polese 2005).

[95] 'Localisation' economies refer to the between-industry specific economies, which are also called Marshallian scale economies (Polese, 2005).

that are essential to technological innovation than the smaller ones. The level of urbanisation differs across space because only a few regions are able to attract investments in innovation and to acquire production capacity (Scott and Storper, 2003: 584). Uneven densities of agglomerations can influence the overall rates of regional economic growth through locational interdependencies. Additionally, the particular patterns of agglomeration vary widely depending on historical path dependencies .(Fujita et al., 1999).

To sum up, conventional theories on the positive or negative relationship between urbanisation and economic growth have favoured the view that a circular causation between growth and a concentration of economic activities sets in. However, the causal link between these two processes is not clear cut (Jacobs, 1970), as urbanisation and economic growth seem so interconnected (Henderson, 2003). The dominant role of cities is the formation of new ideas, new initiatives and new firms, through the generation of strong systems of externalities. Cities are critical foundations of the regional economic development process. Urbanisation is a fundamental and ambiguous constituent of economic growth.

7.2.3.2 Geographical Variables such as Latitude

Latitude may be an important source of economic growth either directly or indirectly through its role in shaping the distribution of European income and education. The growth-latitude relationship has, in fact, been adopted in an international setting. A number of cross-country studies have found latitude to be an important factor in accounting for differences in cross-country economic growth rates. Considering latitude as a good proxy for the effect of a region's climate on its level of productive efficiency, Gallup et al. (1999), Masters and McMillan (2001) and Sachs et al. (2001) have found that the tropical climate zones are confronted with high rates of infectious disease and low agricultural productivity. Nordhaus (1993) and Hall and Jones (1999), on the other hand, find that latitude contributed little to economic growth.

7.2.3.3 Some Institutional Variables

The aim of this next subsectionis to investigate the effects of the welfare state, religion and family structure on growth.

(1) The Welfare State and Growth

Many scholars (i.e. Atkinson, 1995; Fic and Ghate, 2005) argue that the expansion of welfare state regimes is one of the elements found to be responsible for slow economic growth, while contracting welfare state regimes are associated with high economic growth. Other scholars (i.e. Herce et al., 2001), by contrast, have found a positive correlation between the welfare state and the economic growth. The positive benefits provided by the welfare state are the provision of security, poverty alleviation, income redistribution and expenditures on healthcare and education. The major criticisms are based on the fact that the welfare state introduces undesired rigidity in the functioning of labour markets, increases the size of government at the risk of inefficiency and its structure leads to disincentives (Atkinson, 1995). The funding of the welfare state programmes augments the amount of revenue to be raised, and so the magnitude of tax distortions. Thus, the welfare programmes may lead to cumulative deficits and mounting public debts (Dreze and Malinvaud, 1994: 95). It is difficult to disentangle the mixture of incentives and disincentives of the welfare state because it is a conglomerate of different targeted programmes (Herce et al., 2001). The expansion of the welfare state is a political decision that has an impact on the allocation of resources (Sandmo, 1995; Romer, 2003). A retrenchment in state spending on social security is, in some cases, necessary, despite the pressure for redistributive spending.

(2) Religion and Growth

Can religious beliefs and behaviours affect a society's economic growth? Do cultural factors explain the inter-regional differences in rates of economic development? The mechanism behind the religion and growth relationship is that religious beliefs and behaviours affect certain cultural values, attitudes and beliefs, which, in turn, influence one's economic decision-making and, thus, economic outcomes (Mangeloja, 2005). Less empirical evidence has been produced on the relationship between religion and growth. Weber (1930) first introduced the relationship between religion and growth when he wrote about a positive relationship between Protestantism and growth. Based on a cross-national study of 63 former colonies, Grier (1997) found evidence that Protestantism is positively related to economic growth. Other scolars (i.e. Morse, 1964; Harrison, 1985) have highlighted the negative correlation between Catholicism and economic progress. They argue that the characteristics of Catholicism make it less conducive to the work ethic and economic development than Protestantism. Blum and Dudley (2001), in endeavouring to explain urban growth in early-modern Europe (between 1500 and 1750), note falling wages in Catholic cities and rising wages in Protestant cities.

(3) Family Structure and Growth

Does the family structure affect economic growth directly or indirectly through income and educational inequalities? Family structure is shaped by marriage, divorce, fertility and childrearing, which influence the socioeconomic activities of a person. Taken on average, those activities may reflect regional economic growth rates. Additionally, family structure is one of the most important determinants of achievement motivation and skills, and thus a determinant of productivity and growth (Elder, 1965). Greif (2006), for example, has shown that family structure and institutions are the foundations of economic growth.

7.3 Regression Results: Growth and Income and Educational inequality

This section explores the impact of inequality in income and education on regional economic growth. It is given by the following model.

$$GGR2I_{it} = \beta_1' Incpc_{it} + \beta_2' IncIneq_{it} + \beta_3' EducAtt_{it} + \beta_4' EducIneq_{it} + \beta_5' x_{it} + u_{it}$$

with i denoting regions ($i = 1,...,N$) and t time ($t = 1,...,3$);[96] $GGR2I_{it}$ is regional economic growth; $Incpc_{it}$ is income per capita; $IncIneq_{it}$ is income inequality; $EducAtt_{it}$ is educational attainment; $EducIneq_{it}$ is educational inequality; x_{it} is a vector of control variables (see Table 6.2 including the transport infrastructure variables: road and rail infrastructure); $\beta_{1,...,5}$ are coefficients; and u_{it} is the composite error.

The estimates of growth equations are pooled OLS, FEs and REs. To evaluate which technique is optimal, it is necessary to consider the relationship between the unobserved effect and the regressors.

(1) Introducing into the model *the distribution of education level completed*, the p-values of Breusch and Pagan's Lagrange multiplier test accept the validity of the pooled OLS estimates. Hence, the unobserved effect is uncorrelated with the explanatory

96 $t = 1$ denotes 1996, $t = 2$ denotes 1998 and $t = 3$ denotes 2000.

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). Table 7.1 depicts the OLS regression results when independent variables are the income per capita of the population as a whole (IMN), income inequality for the population as a whole $(IGE1)$, average education level completed (EMN) and inequality in education level completed $(EGE1)$, while Table 7.2 shows the OLS results when independent variables are income per capita of normally working people (NMN), income inequality for normally working people $(NGE1)$, average education level completed (EMN) and inequality in education level completed $(EGE1)$. The FEs and REs results of the former model are reported in Appendices A7.1 and A7.3, respectively; whereas, the FEs and REs results of the latter model are reported in Appendices A7.2 and A7.4.

(2) Introducing into the model *the distribution of the age at which the highest education level was completed*, the statistical evidence favours the FEs estimates. Additionally, the p-values of Hausman's test accept the GLS estimator as an appropriate alternative to the FEs estimator. Table 7.3 depicts the OLS, FEs and REs results when independent variables are income per capita $(IMN \text{ and } NMN)$, income inequality $(IGE1 \text{ and } NGE1)$, the average age at which the highest education level was completed (AMN) and inequality in the respective age $(AGE1)$, only. The OLS, FEs and REs results of the model, which also includes the control variables, are reported in Appendix A7.5.

Finally, there is not much difference between the significance of the homoskedasticity and the heteroskedasticity consistent covariance matrix estimator, showing that the determinants of regional economic growth are robust to the model specification about the error term.

Table 7.1: OLS: Dependent Variable is GGR2I and Independent Variables are IMN_LN, IGE1, EMN and EGE1

	(1) (FEs)	(2)	(3)	(4)	(5)	(6)	(7)
IMN_LN	-0.0480 (0.0208)** _(0.0213)**_		0.0011 (0.0114) _(0.0153)_	0.0011 (0.0114) _(0.0153)_	0.0022 (0.0118) _(0.0157)_	0.0028 (0.0117) _(0.0163)_	-0.0013 (0.0130) _(0.0172)_
IGE1	0.1697 (0.0701)** _(0.0618)***_		0.0644 (0.0236)*** _(0.0252)**_	0.0635 (0.0244)** _(0.0258)**_	0.0575 (0.0289)** _(0.0278)**_	0.1031 (0.0308)*** _(0.0292)***_	0.0981 (0.0338)*** _(0.0320)***_
EMN		0.0542 (0.0173)*** _(0.0160)***_	0.0782 (0.0196)*** _(0.0198)***_	0.0778 (0.0198)*** _(0.0201)***_	0.0804 (0.0209)*** _(0.0213)***_	0.0559 (0.0228)** _(0.0243)**_	0.0635 (0.0229)*** _(0.0235)***_
EGE1		0.0625 (0.0114)*** _(0.0119)***_	0.0644 (0.0122)*** _(0.0122)***_	0.0645 (0.0123)*** _(0.0125)***_	0.0666 (0.0134)*** _(0.0135)***_	0.0604 (0.0142)*** _(0.0161)***_	0.0613 (0.0151)*** _(0.0165)***_
AGE				-0.0002 (0.0013) _(0.0013)_	-0.0004 (0.0014) _(0.0013)_	0.0005 (0.0014) _(0.0014)_	-0.0002 (0.0014) _(0.0014)_
LFSTOCK					-0.0222 (0.0575) _(0.0544)_		
ECACRA						0.0015 (0.0007)** _(0.0008)*_	
UNEM							-0.0811 (0.1013) _(0.0885)_
INACTIVE							
ECACRF							0.0008 (0.0006) _(0.0007)_
ROAD (fixed)							
RAIL (fixed)							
URBANDPAV (fixed)							
LAT (fixed)							
DWSLIB							
DWSCORP							
DWSRES							
DRLCATH							
DRLORTH							
DRLANGL							
DFNC							
DFSC							
CONSTANT	0.1491 (0.0562)*** _(0.0580)**_	0.0105 (0.0214) _(0.0208)_	-0.0365 (0.0401) _(0.0442)_	-0.0257 (0.0764) _(0.0721)_	-0.0110 (0.0855) _(0.0752)_	-0.1447 (0.0899) _(0.0815)*_	-0.0544 (0.0933) _(0.0916)_
ADJ R-SQ	0.0533	0.1129	0.1327	0.1298	0.1273	0.1647	0.1546
OBS.	306	298	298	298	298	270	270
LM TEST (p-value)	4.94 (0.0262)	0.20 (0.6536)	0.02 (0.8845)	0.03 (0.8624)	0.04 (0.8482)	0.08 (0.7840)	0.08 (0.7818)
HAUSMAN TEST (p-value)	6.11 (0.0471)	3.89 (0.1428)	18.89 (0.0008)	25.24 (0.0001)	30.23 (0.0000)	27.31 (0.0001)	44.31 (0.0000)

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
IMN_LN	0.0000 (0.0117) _(0.0171)_	0.0390 (0.0244) _(0.0386)_	-0.0180 (0.0203) _(0.0202)_	-0.0028 (0.0136) _(0.0173)_	-0.0181 (0.0162) _(0.0191)_	0.0096 (0.0146) _(0.0203)_	-0.0044 (0.0161) _(0.0203)_
IGE1	0.0749 (0.0345)** _(0.0323)_**	0.1384 (0.0474)*** _(0.0613)_**	0.1409 (0.0476)*** _(0.0439)_***	0.1045 (0.0379)*** _(0.0395)_***	0.1313 (0.0347)*** _(0.0313)_***	0.0918 (0.0356)** _(0.0320)_***	0.1021 (0.0361)*** _(0.0315)_***
EMN	0.0726 (0.0228)*** _(0.0233)_***	0.0630 (0.0479) _(0.0605)_	0.0492 (0.0292)* _(0.0314)_	0.0634 (0.0229)*** _(0.0236)_***	0.0237 (0.0273) _(0.0297)_	0.0290 (0.0282) _(0.0289)_	0.0623 (0.0242)** _(0.0240)_**
EGE1	0.0631 (0.0140)*** _(0.0157)_***	0.0410 (0.0245)* _(0.0225)_*	0.0350 (0.0194)* _(0.0210)_*	0.0619 (0.0152)*** _(0.0166)_***	0.0384 (0.0167)** _(0.0201)_*	0.0502 (0.0180)*** _(0.0212)_**	0.0602 (0.0158)*** _(0.0172)_***
AGE	-0.0025 (0.0017) _(0.0015)_*		0.0000 (0.0018) _(0.0019)_	-0.0002 (0.0014) _(0.0015)_	0.0011 (0.0015) _(0.0015)_	0.0000 (0.0015) _(0.0016)_	-0.0001 (0.0015) _(0.0015)_
LFSTOCK							
ECACRA							
UNEM			-0.1199 (0.1718) _(0.1486)_	-0.0808 (0.1015) _(0.0891)_	-0.0097 (0.1127) _(0.1091)_	0.0646 (0.1142) _(0.1028)_	-0.0862 (0.1075) _(0.0925)_
INACTIVE	0.2355 (0.0890)*** _(0.0778)_***						
ECACRF	0.0017 (0.0006)*** _(0.0007)_**		0.0018 (0.0008)** _(0.0008)_**	0.0008 (0.0006) _(0.0007)_	0.0005 (0.0007) _(0.0007)_	0.0010 (0.0006) _(0.0007)_	0.0008 (0.0007) _(0.0008)_
ROAD (fixed)		0.2324 (0.4618) _(0.4617)_					
RAIL (fixed)		-0.4222 (0.2435)* _(0.2475)_*					
URBANDPAV (fixed)			0.0315 (0.0167)* _(0.0166)_*				
LAT (fixed)				0.0003 (0.0008) _(0.0010)_			
DWSLIB					0.0087 (0.0146) _(0.0189)_		
DWSCORP					-0.0159 (0.0137) _(0.0169)_		
DWSRES					-0.0422 (0.0213)** _(0.0230)_*		
DRLCATH						0.0066 (0.0091) _(0.0074)_	
DRLORTH						0.0296 (0.0175)* _(0.0153)_*	
DRLANGL						0.0211 (0.0098)** _(0.0108)_*	
DFNC							-0.0007 (0.0137) _(0.0173)_
DFSC							-0.0042 (0.0133) _(0.0146)_
CONSTANT	-0.1011 (0.0830) _(0.0765)_	-0.1030 (0.0814) _(0.1024)_	-0.0724 (0.1225) _(0.1172)_	-0.0701 (0.1022) _(0.1053)_	-0.0125 (0.1004) _(0.0950)_	-0.0802 (0.0943) _(0.0883)_	-0.0496 (0.0986) _(0.0930)_
ADJ R-SQ	0.1746	0.0716	0.1512	0.1518	0.1941	0.1680	0.1484
OBS.	270	114	163	270	270	270	270
LM TEST (p-value)	0.00 (0.9903)	1.93 (0.1642)	0.42 (0.5194)	0.09 (0.7598)	0.00 (0.9934)	0.03 (0.8594)	0.11 (0.7455)
HAUSMAN TEST (p-value)	34.96 (0.0000)						

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

Table 7.2: OLS: Dependent Variable is GGR2I and Independent Variables are NMN_LN, NGE1, EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NMN_LN	-0.0136 (0.0076)* *(0.0095)*		0.0009 (0.0116) *(0.0156)*	0.0010 (0.0117) *(0.0156)*	0.0031 (0.0117) *(0.0158)*	0.0027 (0.0120) *(0.0166)*	0.0030 (0.0130) *(0.0169)*
NGE1	0.1450 (0.0346)*** *(0.0356)****		0.0980 (0.0376)** *(0.0408)***	0.0974 (0.0376)** *(0.0407)***	0.0853 (0.0384)** *(0.0407)***	0.1084 (0.0402)*** *(0.0419)***	0.1022 (0.0416)** *(0.0434)***
EMN		0.0542 (0.0173)*** *(0.0160)****	0.0528 (0.0176)*** *(0.0180)****	0.0524 (0.0176)*** *(0.0180)****	0.0694 (0.0209)*** *(0.0213)****	0.0446 (0.0231)* *(0.0245)**	0.0550 (0.0233)** *(0.0238)***
EGE1		0.0625 (0.0114)*** *(0.0119)****	0.0529 (0.0132)*** *(0.0142)****	0.0539 (0.0133)*** *(0.0145)****	0.0614 (0.0142)*** *(0.0151)****	0.0589 (0.0150)*** *(0.0174)****	0.0630 (0.0154)*** *(0.0174)****
AGE				-0.0011 (0.0013) *(0.0013)*	-0.0013 (0.0013) *(0.0012)*	-0.0009 (0.0013) *(0.0013)*	-0.0009 (0.0014) *(0.0014)*
LFSTOCK					-0.0682 (0.0455) *(0.0443)*		
ECACRA						0.0004 (0.0005) *(0.0006)*	
UNEM							-0.0010 (0.0987) *(0.0882)*
INACTIVE							
ECACRF							0.0000 (0.0005) *(0.0005)*
ROAD (fixed)							
RAIL (fixed)							
URBANDPAV (fixed)							
LAT (fixed)							
DWSLIB							
DWSCORP							
DWSRES							
DRLCATH							
DRLORTH							
DRLANGL							
DFNC							
DFSC							
CONSTANT	0.1032 (0.0248)*** *(0.0303)****	0.0105 (0.0214) *(0.0208)*	-0.0054 (0.0394) *(0.0433)*	0.0460 (0.0705) *(0.0620)*	0.0668 (0.0717) *(0.0608)*	0.0072 (0.0751) *(0.0644)*	0.0183 (0.0872) *(0.0847)*
ADJ R-SQ	0.0962	0.1129	0.1271	0.1264	0.1301	0.1498	0.1448
OBS.	306	298	298	298	298	270	270
LM TEST (p-value)	2.06 (0.1510)	0.20 (0.6536)	0.03 (0.8644)	0.07 (0.7928)	0.05 (0.8147)	0.47 (0.4933)	0.52 (0.4712)
HAUSMAN TEST (p-value)	2.77 (0.2506)	3.89 (0.1428)	10.75 (0.0295)	18.66 (0.0022)	25.98 (0.0002)	23.32 (0.0007)	39.97 (0.0000)

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**), and (***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
NMN_LN	-0.0022 (0.0120) *(0.0175)*	0.0267 (0.0227) *(0.0348)*	-0.0141 (0.0206) *(0.0217)*	0.0044 (0.0135) *(0.0168)*	-0.0066 (0.0158) *(0.0180)*	0.0141 (0.0143) *(0.0194)*	0.0072 (0.0156) *(0.0189)*
NGEI	0.0830 (0.0411)** *(0.0418)***	0.1787 (0.0629)*** *(0.0689)***	0.1601 (0.0542)*** *(0.0559)****	0.0963 (0.0446)** *(0.0519)**	0.1278 (0.0435)*** *(0.0448)****	0.0730 (0.0444) *(0.0486)*	0.1005 (0.0452)** *(0.0431)***
EMN	0.0666 (0.0233)*** *(0.0234)****	0.0157 (0.0444) *(0.0602)*	0.0465 (0.0294) *(0.0315)*	0.0556 (0.0234)** *(0.0243)***	0.0186 (0.0275) *(0.0305)*	0.0293 (0.0285) *(0.0297)*	0.0590 (0.0244)** *(0.0242)***
EGEI	0.0594 (0.0148)*** *(0.0171)****	0.0121 (0.0248) *(0.0219)*	0.0391 (0.0198)* *(0.0228)**	0.0625 (0.0155)*** *(0.0173)****	0.0426 (0.0170)** *(0.0216)**	0.0570 (0.0183)*** *(0.0230)***	0.0650 (0.0158)*** *(0.0176)****
AGE	-0.0034 (0.0016)** *(0.0014)***		-0.0011 (0.0019) *(0.0020)*	-0.0008 (0.0014) *(0.0014)*	-0.0002 (0.0015) *(0.0014)*	-0.0008 (0.0015) *(0.0015)*	-0.0010 (0.0015) *(0.0014)*
LFSTOCK							
ECACRA							
UNEM			0.0867 (0.1660) *(0.1398)*	-0.0063 (0.0999) *(0.0912)*	0.0893 (0.1076) *(0.1040)*	0.1160 (0.1088) *(0.0969)*	-0.0076 (0.1022) *(0.0893)*
INACTIVE	0.2570 (0.0883)*** *(0.0793)****						
ECACRF	0.0011 (0.0006)** *(0.0006)**		0.0007 (0.0007) *(0.0007)*	0.0001 (0.0005) *(0.0006)*	-0.0006 (0.0006) *(0.0007)*	0.0003 (0.0005) *(0.0005)*	0.0000 (0.0006) *(0.0007)*
ROAD (fixed)		0.5623 (0.4483) *(0.4625)*					
RAIL (fixed)		-0.4232 (0.2396)* *(0.2356)**					
URBANDPAV (fixed)			0.0221 (0.0165) *(0.0163)*				
LAT (fixed)				-0.0003 (0.0008) *(0.0010)*			
DWSLIB					0.0015 (0.0153) *(0.0189)*		
DWSCORP					-0.0233 (0.0145) *(0.0174)*		
DWSRES					-0.0370 (0.0222)* *(0.0242)*		
DRLCATH						0.0081 (0.0091) *(0.0073)*	
DRLORTH						0.0362 (0.0177)** *(0.0160)***	
DRLANGL						0.0193 (0.0098)* *(0.0109)**	
DFNC							0.0047 (0.0145) *(0.0176)*
DFSC							0.0057 (0.0126) *(0.0133)*
CONSTANT	-0.0173 (0.0739) *(0.0678)*	-0.0173 (0.0693) *(0.0836)*	0.0406 (0.1173) *(0.1136)*	0.0263 (0.0899) *(0.0885)*	0.0967 (0.1015) *(0.0978)*	-0.0158 (0.0893) *(0.0837)*	0.0088 (0.0983) *(0.0928)*
ADJ R-SQ	0.1716	0.0638	0.1314	0.1420	270	270	270
OBS.	270	114	163	270	0.1731	0.1585	0.1397
LM TEST (p-value)	0.05 (0.8163)	1.07 (0.3016)	1.62 (0.2035)	0.44 (0.5092)	0.31 (0.5751)	0.21 (0.6434)	0.35 (0.5513)
HAUSMAN TEST (p-value)	31.54 (0.0000)						

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

Table 7.3: OLS, FEs and REs: Dependent Variable is GGR2I and Independent Variables are IMN_LN, IGE1, NMN_LN, NGE1, AMN and AGE1

	REGRESSION 1			REGRESSION 2			REGRESSION 3		
	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs	(a) OLS	(b) FEs	(c) REs
IMN_LN				-0.0216 (0.0103)** *(0.0122)**	-0.0249 (0.0197) *(0.0212)*	-0.0203 (0.0106)* *(0.0125)*			
IGE1				0.0234 (0.0242) *(0.0241)*	0.1764 (0.0686)** *(0.0587)****	0.0279 (0.0255) *(0.0250)*			
NMN_LN							-0.0221 (0.0102)** *(0.0129)**	-0.0179 (0.0199) *(0.0226)*	-0.0217 (0.0103)** *(0.0130)**
NGE1							0.1260 (0.0388)*** *(0.0412)****	0.1019 (0.0711) *(0.0639)*	0.1252 (0.0396)*** *(0.0415)****
AMN	-0.0059 (0.0009)*** *(0.0008)****	-0.0043 (0.0057) *(0.0041)*	-0.0059 (0.0010)*** *(0.0009)****	-0.0031 (0.0013)** *(0.0013)***	-0.0010 (0.0058) *(0.0043)*	-0.0031 (0.0014)** *(0.0013)***	-0.0024 (0.0013)* *(0.0013)**	-0.0040 (0.0058) *(0.0042)*	-0.0025 (0.0013)* *(0.0013)**
AGE1	0.0083 (0.1167) *(0.1212)*	0.0893 (0.4807) *(0.4294)*	0.0102 (0.1248) *(0.1301)*	-0.3811 (0.1734)** *(0.2017)**	-0.1382 (0.4869) *(0.5100)*	-0.3727 (0.1818)** *(0.0367)****	-0.3809 (0.1603)** *(0.1910)***	0.0423 (0.4876) *(0.4698)*	-0.3732 (0.1642)** *(0.1962)**
CONSTANT	0.2094 (0.0173)*** *(0.0150)****	0.1772 (0.1019)* *(0.0763)***	0.2092 (0.0186)*** *(0.0162)****	0.2157 (0.0305)*** *(0.0353)****	0.1144 (0.1110) *(0.0931)*	0.2106 (0.0321)*** *(0.2143)**	0.1913 (0.0306)*** *(0.0393)****	0.1964 (0.1095)* *(0.0951)***	0.1910 (0.0312)*** *(0.0397)****
ADJ R-SQ	0.1284	0.0034		0.1517	0.0515		0.1796	0.0196	
OBS.	263			263			263		
LM TEST (p-value)	6.64 (0.0100)			5.17 (0.0230)			3.10 (0.0782)		
HAUSMAN TEST (p-value)	0.15 (0.9286)			6.85 (0.1441)			1.10 (0.8936)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

7.3.1 Growth and Income Inequality

The analysis performed here addresses the following model.

$$GGR2I_{it} = \beta_1' Incpc_{it} + \beta_2' IncIneq_{it} + u_{it}$$

Regression 1 of Table 7.1 and Table 7.2 illustrates the combined impact of the natural logarithm of income per capita, as in Forbes' (2000) empirical study, and income inequality on regional economic growth.

The *elasticity coefficient on income per capita* for both models (either for the population as a whole (IMN_LN) or for normally working people (NMN_LN)) is negative. It is likely to show some convergence in the EU. Poor regions may grow faster than rich ones (Solow, 1956; Swan, 1956; Mankiw et al., 1992; Jones, 1997, 1998).

The findings also show the positive impact of *income inequality* (either for the population as a whole $(IGE1)$ or for normally working people $(NGE1)$) on regional economic growth.[97] Inequality seems to be fundamentally good for incentives and therefore should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). Public polices aimed at reducing income inequality may not be strong enough to provide negative incentives for economic efficiency that may harm growth. The positive inequality-growth relationship is indicative of a *laissez-faire* economy, in which government intervention is minimal. The results may support the view of classical economists who claim that a certain level of income inequality favours capital accumulation, because the rich agents have a higher marginal propensity to save compared to the poor, increasing aggregate savings and growth. The results also are inconsistent with the modern approach. More specifically, between 1996 and 2002, the European economy is in the later stages of economic development. At this stage, equality stimulates investment in human capital, which promotes growth, as human capital accumulation is greater if it is shared by the largest segment of the society. Therefore, according to the modern approach, the inequality-growth relationship does not have the expected sign. Income inequality has decreased slightly between 1995 and 2000. To this end, Champernowne and Cowell (1998) argue that once people are

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97 Considering the model $GGR2I_{it} = \beta_1' Incpc_{it} + \beta_2' IncIneq_{it} + \beta_5' x_{it} + u_{it}$, the elasticity coefficient on income per capita is very sensitive to the inclusion of additional variables, while the coefficient on income inequality is robust (the results are provided on request).

accustomed to a degree of comfort they will regard it as a hardship to return to an earlier and lower standard of living. Thus, a reduction in income inequality (but usually rapid) is likely to slow down economic progress, highlighting the difficulty of the adjustment process. Finally, considering the political economy models, the higher the income inequality, the higher the rate of taxation, the greater the expenditure on public education programmes, the higher the public investment in human capital and the higher the (national) economic growth (Aghion and Bolton, 1990; Saint-Paul and Verdier, 1993).

7.3.2 Growth and Educational Inequality

The analysis performed here addresses the combined impact of educational attainment and inequality as in the following model.

$$GGR2I_{it} = \beta_3' EducAtt_{it} + \beta_4' EducIneq_{it} + u_{it}$$

(1) Regression 2 of Table 7.1 (or Table 7.2) illustrates the following model.

$$GGR2I_{it} = \beta_3' EMN_{it} + \beta_4' EGE1_{it} + u_{it}$$

The positive coefficient on *educational attainment* (*EMN*) most probably reflects the fact that education is one of the most powerful instruments known for laying the basis for sustained growth (Hannum and Buchmann, 2005). This finding is consistent both with Lucas' (1988) theory, which is inspired by Schultz's (1963) and Becker's (1964) theories, and also with the theory developed by Nelson et al. (1966), which is a rival to the Schumpeterian growth literature (Schumpeter, 1934), as it is based on the idea that growth is primarily driven by education. Although the capacity of a region to absorb or to generate technical progress is basically determined by its institutional environment, human capital stock is also a critical factor in determining the productive capacity of the regional economy, because it determines the region's ability to generate its own progress and it is an ingredient in determining the region's ability to generate its technical progress (Armstrong and Taylor, 2000). The positive coefficient also highlights the major role of education not only in increasing the individual's capacity, but also in facilitating the process of adaptation to new technologies so as to speed up the diffusion of technology throughout the EU (Aghion et al., 1998). Education seems to allow those European regions with currently less advanced technologies to learn more from advanced regions and thereby help the former to achieve a higher degree of productivity improvement when innovating, and thus a higher growth rate. The impact of education on growth may not reflect the way that the education system serves to help individual growth, but rather to sort individuals to fill slots in the labour market (Hannum and Buchmann, 2005). Education also has implications for the optimal capital structure. Technologically advanced societies build more human capital relative to physical capital (Aghion et al., 1998).

The positive coefficient on *educational inequality* ($EGE1$) most likely denotes the fact that inequality is fundamentally good for incentives and is viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998) as most people require qualifications that are not possessed by everyone.[98] Hence, inequality enables people to increase their returns on investment in human capital by obtaining higher educational degrees. Moreover, the existence of less talented and educated people implies incentives to individuals to seize the higher returns to their skills (Voitchovsky, 2005). Educational inequality may enable members of the more highly-educated segments of society to increase their investment in human capital, while equality may trap the society as a whole at a low level of investment in human capital (Galor and Tsiddon, 1997a: 94).

(2) Regression 1 of Table 7.3 illustrates the following model.

$$GGR2I_{it} = \beta_3{}'AMN_{it} + \beta_4{}'AGE1_{it} + u_{it}$$

Educational attainment (AMN) yields a negative sign in growth regressions. According to de la Fuente and Domenech (2006: 5), the 'wrong' result has fuelled a growing scepticism over the role of education in the growth process. They also mention that a negative sign for the educational attainment variable may simply reflect the omission of some other structural factors that may account for the growth slowdown. Regression 1 also shows the insignificant coefficient on *educational inequality* ($AGE1$).[99]

[98] Considering the model $GGR2I_{it} = \beta_3{}'EMN_{it} + \beta_4{}'EGE1_{it} + \beta_5{}'x_{it} + u_{it}$, the coefficients on educational attainment and inequality are robust (the results are provided on request).

[99] Considering the model $GGR2I_{it} = \beta_3{}'AMN_{it} + \beta_4{}'AGE1_{it} + \beta_5{}'x_{it} + u_{it}$, the coefficients on educational attainment and inequality are negative, but very sensitive to the econometric estimation (OLS, FEs and REs estimates) and to the inclusion of different control variables (the results are provided on request).

7.3.3 Growth and Income and Educational Inequality

(1) Regressions 3–14 of Table 7.1 and Table 7.2 show the combined impact of income inequality (for the population as a whole and for normally working people, respectively) and educational inequality, measured by *inequality in the education level completed* $(EGE1)$, on regional economic growth. They depict the following model.

$$GGR2I_{it} = \beta_1' Incpc_{it} + \beta_2' IncIneq_{it} + \beta_3' EMN_{it} + \beta_4' EGE1_{it} + \beta_5' x_{it} + u_{it}$$

The findings show the that the impact of income per capita (either (IMN_LN) or (NMN_LN)) on growth is not clear, because the elasticity coefficient on income per capita is statistically insignificant. The coefficient on educational attainment (EMN), on the other hand, is positive, significant and robust to the inclusion of additional control variables. The results also show that the higher the income and educational inequality, the higher the growth rate. This finding is also robust.

Regression 4 displays the introduction of population ageing (AGE). The negative and statistically significant coefficient may show that older people are less productive than younger ones, because they differ in their level of technology adoption and in work effort, since the former are the primary adopters and beneficiaries of new technologies, they work more hours and they are able to concentrate more on the job (Cheal, 2000; Galenson and Weinberg, 2000, 2001).

Regressions 5 and 6 control for access to work: the percentage of normally working respondents $(LFSTOCK)$ and the economic activity rate of total population $(ECACRA)$, respectively. The results show a positive coefficient on the latter proxy for access to work (in Table 7.1 only). This is likely to depict that high participation in the labour market contributes to a competitive economic environment, which promotes allocative efficiency (Azzoni and Silveira-Neto, 2005).

Regressions 7 and 8 introduce unemployment $(UNEM)$ and inactivity levels $(INACTIVE)$, as well as the female participation in the labour market $(ECACRF)$. The positive coefficient on inactivity accords well with the theoretical work of Hall (1991) and Caballero and Hammour (1994), which emphasise that recession may stimulate growth. More specifically, inactivity may stimulate efficiency gains by causing less efficient firms to exit, and may encourage firms to adopt reorganising investments and innovative activities. The impact of women's access to work on growth is positive and statistically significant. Although women usually hold the majority of low-income jobs and have less continuous employment than men, their participation in the labour market increases the economic efficiency.

Regression 9 examines the influence of the transport infrastructure on growth. While the coefficient on road infrastructure $(ROAD)$ is not statistically significant, the coefficient on rail infrastructure $(RAIL)$ is negative and significant. The negative impact of the rail infrastructure is likely to show its limited benefits. European regions may face constraints on development, because the nature of rail infrastructures tends to mean that there are capacity limits, beyond which negative externalities (i.e. delays) start to dominate. The rail infrastructure may, on average, have exceeded the critical threshold level. However, bearing in mind that data for only a few regions were available, some caution is called for in the interpretation of the results.

Regressions 10 and 11 test for the impact of urbanisation $(URBANDPAV)$ and latitude (LAT) on regional economic growth. Regression 10 of Table 7.1 shows that the higher the urbanisation level within a region, the higher the growth rate. Urbanisation seems to spur economic growth, because city-regions are full of technological and pecuniary externalities. Cities allow goods, ideas and people to come together for the purposes of exchange and production (Polese, 2005). This, in turn, allows regions to reap the gains from trade and specialisation, enhancing growth. Additionally, cities foster and facilitate flows of local knowledge, the creation of dense social networks and the production of behavioural and cultural change. All of those factors promote development, innovation and growth. The coefficient on latitude, on the other hand, is not statistically significant in either table.

Regressions 12–14 examine the influence of qualitative time-invariant variables. The findings show that regional growth is lowest in 'residual' countries, according to the welfare state; Anglican areas have the highest growth rate; while the family structure does not matter for growth. Finally, considering the standardised coefficients for the above regressions (Appendix A7.6), income inequality and women's access to work explain the largest variation in the growth rate.

(2) Measuring educational inequality as *inequality in age at which the highest education level was completed* $(AGE1)$, Regressions 2–3 of Table 7.3 show the combined impact of income inequality (for the population as a whole $(IGE1)$ and for normally working

people $(NGE1)$, respectively) and educational inequality on regional economic growth. The model is:

$$GGR2I_{it} = \beta_1' Incpc_{it} + \beta_2' IncIneq_{it} + \beta_3' AMN_{it} + \beta_4' AGE1_{it} + u_{it}$$

The p-values of Breusch and Pagan's Lagrange multiplier test and of Hausman's test favour both the FEs and the REs results.

In Regression 2, which considers *income inequality for the population as a whole* $(IGE1)$, the FEs results show that income inequality matters for growth, but the remaining three coefficients are insignificant. The REs results, on the other hand, show a completely different view. Both income per capita and educational attainment have a negative sign, the coefficient on income inequality is statistically insignificant, while the coefficient on educational inequality does not have the expected sign. Nevertheless, the negative coefficient on educational inequality most probably reflects the fact that the accumulated knowledge of the highly-educated individuals trickles down to the less-educated ones via the technological progress in production (Galor and Tsiddon, 1997a). Additionally, the lower the educational inequality, the greater the educational opportunities for the poor, the more job chances there are, the better the allocation and efficiency of resources and the higher the regional economic development.

In Regression 3, which considers *income inequality for normally working people* $(NGE1)$, the FEs results show that neither income and educational distributions do not matter for growth. However, the REs results illustrate the positive coefficient on income inequality, the negative coefficients on educational attainment and educational inequality and the negative elasticity coefficient on income per capita. The REs specification demonstrates that income inequality and educational equality stimulate growth.

Regressions 2 and 3 show some convergence in the EU and the fact that income inequality and educational equality boost growth. The impact of control variables on growth are reported in Appendix A7.5, because their coefficients are not sensitive to two proxies for human capital.

To sum up, when independent variable is inequality in the education level completed $(EGE1)$, the statistical evidence supports the OLS results, which show that the higher the income and educational inequality, the higher the growth rate. However, when independent variable is inequality in the age at which the highest education level was completed ($AGE1$), the statistical evidence is mostly in support of the FEs and REs results (and in some cases the OLS results — see Appendix A7.5) which illustrate that the higher the income inequality and the lower the educational inequality, the lower the growth rate. Finally, no matter how income and educational inequalities are measured, the low adjusted R-squared show that income and human capital variables account for a small proportion of the variation in regional economic growth levels.

7.4 Causality

The theoretical arguments advocate a causal link between inequality and economic growth. Still lacking in knowledge on the causality issue, the studies are less useful guide for regional economic policy. Nevertheless, the empirical impact of growth on inequality has long attracted less attention among the economists than the reverse impact. Mocan (1999), for instance, argued that growth is not necessarily associated with an improvement in income inequality, because growth can coexist with increased unemployment. Aghion et al. (1999), on the other hand, found that growth may increase wage inequality, both across and within education cohorts, and that technical change is a crucial factor in explaining this relationship. Finally, Griffin and Khan (1972), Sheahan (1980) and Papanek and Kyn (1986) demonstrated that a high rate of growth increases inequality because it requires great rewards for higher income groups such as inventors, managers and land owners. The question addressed here is: 'does regional economic growth increase income and educational inequality?'.

Table 7.4 displays the OLS, FEs and REs results for the impact of inequality on regional economic growth ($GGR2F$). The statistical evidence is in favour of the FEs models. In Regression 4, additionally, the REs model is an appropriate alternative to the FEs model.

Table 7.4 displays the following results.

Regressions 1–2: The impact of regional economic growth on *income inequality for the population as a whole* is not statistically significant, no matter how educational distribution is measured.

Regressions 3–4: The impact of growth on *income inequality for normally working people* seems to be positive, but sensitive to the inclusion of the human capital proxy and to the model specification. More specifically, while the FEs results show an insignificant coefficient in Regressions 3 and 4, the REs results of Regression 4 yield a positive coefficient. They show that the higher the regional economic growth rate, the higher the income inequality. One possible explanation for that result is that regional trade flows bring in new technologies and ideas, which enhance the productivity of the rich more than that of the poor. The former usually have skills that may be enhanced by the arrival of new technologies, thus increasing their wage relative to that of less-educated workers. However, the regression results must be interpreted with some caution due to the limited time-series analysis (two years). According to Aghion et al. (1999: 1655), the arrival of an embodied technical change will initially raise the transferability of knowledge (because of the generality of the current cutting-edge technology), increasing within-cohort inequality. Nevertheless, this increase would halt once the new technology is so widely spread that all workers have had some experience with it, reducing inequality over the long run.

Regressions 5–8: The impact of growth on *both proxies for educational inequality* is insignificant, no matter which income distribution is considered.

Table 7.4: Causality (1998, 2000)

	REGRESSION 1: IGE1			REGRESSION 2: IGE1			REGRESSION 3: NGE1			REGRESSION 4: NGE1		
	(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	-0.0119 (0.0028)*** (0.0030)***	-0.0008 (0.0036) (0.0040)	-0.0093 (0.0020)*** (0.0021)***	-0.0192 (0.0027)*** (0.0030)***	-0.0022 (0.0028) (0.0032)	-0.0096 (0.0022)*** (0.0026)***						
IGE1												
NMN							0.0002 (0.0014) (0.0016)	0.0022 (0.0027) (0.0037)	-0.0009 (0.0013) (0.0015)	-0.0016 (0.0014) (0.0019)	-0.0016 (0.0021) (0.0029)	-0.0014 (0.0014) (0.0018)
NGE1												
EMN	-0.1922 (0.0562)*** (0.0445)***	0.0113 (0.1217) (0.1389)	-0.2011 (0.0579)*** (0.0565)***				0.0356 (0.0332) (0.0290)	0.1424 (0.1270) (0.1293)	0.0405 (0.0390) (0.0386)			
EGE1	-0.0018 (0.0386) (0.0378)	0.0151 (0.0717) (0.0549)	0.0020 (0.0425) (0.0354)				0.1125 (0.0246)*** (0.0237)***	0.0300 (0.0738) (0.0558)	0.0988 (0.0291)*** (0.0269)***			
AMN				-0.0087 (0.0036)** (0.0040)**	-0.0036 (0.0117) (0.0131)	-0.0155 (0.0040)*** (0.0045)***				-0.0082 (0.0022)*** (0.0024)***	0.0100 (0.0119) (0.0091)	-0.0087 (0.0025)*** (0.0028)***
AGE1				0.5352 (0.5350) (0.5472)	1.3221 (0.6705)* (0.7988)	1.8358 (0.4623)*** (0.5746)***				0.6113 (0.3191)* (0.3316)*	1.1426 (0.6826)* (0.5978)*	0.7496 (0.3290)** (0.3247)**
GGR2F	0.3226 (0.1835)* (0.1659)*	-0.0624 (0.1174) (0.0916)	0.1066 (0.1046) (0.1016)	0.1844 (0.1873) (0.1720)	-0.0642 (0.1342) (0.1109)	0.0708 (0.1243) (0.1075)	0.1565 (0.1149) (0.1171)	-0.0135 (0.1174) (0.0944)	0.1200 (0.0959) (0.0926)	0.2905 (0.1158)** (0.1067)***	0.0137 (0.1359) (0.1127)	0.1741 (0.1058) (0.0918)*
CONSTANT	0.6358 (0.0676)*** (0.0699)***	0.3659 (0.1662)** (0.1794)**	0.6329 (0.0797)*** (0.0751)***	0.7325 (0.0626)*** (0.0687)***	0.4306 (0.2124)** (0.2367)*	0.7009 (0.0713)*** (0.0776)***	0.0915 (0.0443)** (0.0484)*	0.0495 (0.1733) (0.1782)	0.1178 (0.0543)** (0.0560)**	0.3521 (0.0394)*** (0.0452)***	0.0169 (0.2160) (0.1850)	0.3637 (0.0446)*** (0.0529)***
ADJ R-SQ	0.4870	0.0061		0.5190	0.0579		0.2494	0.0189		0.2380	0.0508	
OBS.	204			170			204			170		
LM TEST (p-value)	74.08 (0.0000)			51.57 (0.0000)			40.55 (0.0000)			27.72 (0.0000)		
HAUSMAN TEST (p-value)	10.85 (0.0283)			25.84 (0.0000)			8.93 (0.0629)			6.27 (0.1801)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**) and (***)* denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

	REGRESSION 5: EGE1			REGRESSION 6: EGE1			REGRESSION 7: AGE1			REGRESSION 8: AGE1		
	(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	-0.0159 (0.0053)*** _(0.0050)_***	-0.0149 (0.0048)*** _(0.0041)_***	-0.0098 (0.0032)*** _(0.0026)_***				-0.0034 (0.0004)*** _(0.0004)_***	0.0005 (0.0005) _(0.0006)_	-0.0017 (0.0004)*** _(0.0004)_***			
IGE1	-0.0062 (0.1300) _(0.1276)_	0.0299 (0.1423) _(0.1072)_	-0.0015 (0.1135) _(0.0918)_				0.0113 (0.0113) _(0.0105)_	0.0346 (0.0176)* _(0.0147)_**	0.0444 (0.0119)*** _(0.0103)_***			
NMN				-0.0141 (0.0037)*** _(0.0034)_***	-0.0126 (0.0035)*** _(0.0033)_***	-0.0086 (0.0024)*** _(0.0021)_***				-0.0030 (0.0003)*** _(0.0002)_***	0.0004 (0.0003) _(0.0004)_	-0.0016 (0.0003)*** _(0.0003)_***
NGE1				0.8451 (0.1849)*** _(0.1513)_***	0.0562 (0.1381) _(0.1063)_	0.2250 (0.1290)* _(0.1116)_**				0.0356 (0.0186)* _(0.0167)_**	0.0293 (0.0175)* _(0.0110)_***	0.0412 (0.0168)** _(0.0135)_***
EMN	-0.9710 (0.0806)*** _(0.0893)_***	-1.3111 (0.1091)*** _(0.1849)_***	-1.1372 (0.0586)*** _(0.0767)_***	-0.9068 (0.0647)*** _(0.0606)_***	-1.3483 (0.1097)*** _(0.1922)_***	-1.1371 (0.0527)*** _(0.0646)_***						
EGE1												
AMN							0.0040 (0.0004)*** _(0.0003)_***	0.0032 (0.0019)* _(0.0026)_	0.0036 (0.0006)*** _(0.0005)_***	0.0040 (0.0004)*** _(0.0004)_***	0.0028 (0.0019) _(0.0028)_	0.0032 (0.0006)*** _(0.0005)_***
AGE1												
GGR2F	1.4183 (0.3239)*** _(0.3476)_***	0.0874 (0.1655) _(0.1102)_	0.1506 (0.1544) _(0.1334)_	1.1577 (0.3057)*** _(0.3417)_***	0.0818 (0.1604) _(0.1146)_	0.1505 (0.1558) _(0.1378)_	0.0118 (0.0272) _(0.0246)_	-0.0229 (0.0216) _(0.0201)_	-0.0002 (0.0209) _(0.0184)_	-0.0018 (0.0285) _(0.0258)_	-0.0255 (0.0216) _(0.0207)_	-0.0032 (0.0221) _(0.0203)_
CONSTANT	1.5376 (0.1017)*** _(0.1212)_***	1.9371 (0.1389)*** _(0.2035)_***	1.7380 (0.0908)*** _(0.1020)_***	1.3548 (0.0765)*** _(0.0679)_***	1.9842 (0.1268)*** _(0.1972)_***	1.7042 (0.0677)*** _(0.0775)_***	0.0052 (0.0123) _(0.0127)_	-0.0308 (0.0351) _(0.0446)_	-0.0210 (0.0139) _(0.0135)_	0.0088 (0.0116) _(0.0109)_	-0.0170 (0.0345) _(0.0490)_	-0.0006 (0.0131) _(0.0118)_
ADJ R-SQ	0.7717	0.6406		0.7994	0.6501		0.5598	0.0975		0.5357	0.0884	
OBS.	204			204			170			170		
LM TEST (p-value)	73.66 (0.0000)			66.57 (0.0000)			36.32 (0.0000)			31.20 (0.0000)		
HAUSMAN TEST (p-value)	304.83 (0.0000)			22.66 (0.0001)			64.89 (0.0000)			116.12 (0.0000)		

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator. 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 (1978) test for fixed or random effects.

7.5 Conclusion

As a whole, the results seem to be reasonable and there are socioeconomic theories in the literature that confirm the observed relationships. Although differences in income and educational inequalities explain a small part of the differences in regional economic growth rates, the positive inequality-growth relationship indicates a *laissez-faire* regional economy, in which government intervention is minimal. Income inequality and inequality in the education level completed seem to be fundamentally good for socioeconomic incentives and thus should be viewed as being growth-enhancing (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). For instance, most people require qualifications that are not possessed to everyone. Nevertheless, the relationship between inequality in the age at which the highest education level was completed and regional economic growth is negative, but very sensitive to the model specification. Therefore, considering educational inequality, its impact on growth seems to be sensitive to the definition of human capital. This fuels the growing scepticism over the role of human capital in the growth process (de la Fuente and Domenech, 2006). Besides, school quality is not taken into account in either proxy. The best measurement of human capital would be in terms of education output, but due to the difficulties of obtaining such measures, input measures tend to be used (Sianesi and Van Reenen, 2003). Although the theoretical arguments are in favour of a causal link between inequality and growth, the statistical evidence produced in this chapter does not suggest causality.

The findings indicate that the effect of the average income and human capital on growth is not clear-cut. More specifically, the impact of income per capita is negative, showing some convergence in the EU. However, the elasticity coefficient on income per capita is very sensitive to the inclusion of control variables. The coefficients on educational attainment are sensitive not only to the model specifications (because the OLS estimates are significant, while the FEs ones are not), but also to the definition of human capital (because the OLS coefficients on the average education level completed are positive, while the OLS coefficients on the average age at which the highest education level was completed are negative).

The levels of growth have not evolved differently either in urban and rural areas or in northern and southern areas. More specifically, the impact of urbanisation on growth is positive only when income is considered as the explanatory variable in growth models, but it is insignificant when human capital is taken into account. The impact of latitude on growth is not statistically significant in any of the growth models. Nevertheless, some caution is called for in the interpretation of these results calls due to data limitations. Finally, growth rates do not vary across different welfare state regimes, religious affiliations or family structure clusters.

One of the major difficulties is that multiple direct and indirect linkages exist among income inequality, educational inequality and regional economic growth, and common factors, such as population ageing, also exert an influence upon them. Most control variables seem to both directly and indirectly affect regional economic growth. For instance, the findings show that the lower the population ageing, the higher the growth rate. Young workers not only are the primary adopters and beneficiaries of new technologies, but also work more hours and are able to concentrate more on the job than their older counterparts.

This chapter contributes to two different strands within the field of economic growth: the relationship among income per capita, educational attainment and growth (the first strand); and between inequality and growth (the second strand). To this end, the analysis shows that the second strand outweighs the first.

The findings have important policy implications. Income and human capital inequality are likely to increase growth, but the magnitude of their impact is small. However, increasing inequality does not emerge as a simple remedy for increasing growth due to their direct and indirect linkages. Policy-makers should also take into account that the reverse effect does not seem to be valid. Considerable light can be shed on these issues through further analysis of the ways in which the results are sensitive to the definition of human capital.

Appendix A7

Appendix A7.1: FEs: Dependent Variable is GGR2I and Independent Variables are IMN_LN, IGE1, EMN and EGE1

	(1) (OLS)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(10)	(11)
IMN_LN	-0.0135 (0.0082) _(0.0101)_		-0.0855 (0.0282)*** _(0.0277)_***	-0.0547 (0.0314)* _(0.0320)_*	-0.0403 (0.0318) _(0.0325)_	-0.0304 (0.0348) _(0.0380)_	-0.0098 (0.0341) _(0.0349)_	-0.0152 (0.0347) _(0.0367)_	0.1115 (0.0523)** _(0.0535)_**	0.1318 (0.0349)*** _(0.0400)_***
IGE1	0.0452 (0.0227)** _(0.0252)_*		0.1710 (0.0719)** _(0.0614)_***	0.1453 (0.0722)** _(0.0644)_**	0.0920 (0.0757) _(0.0733)_	0.0921 (0.0825) _(0.0832)_	-0.0027 (0.0835) _(0.0854)_	0.0528 (0.0834) _(0.0868)_	0.0423 (0.1113) _(0.1006)_	-0.0605 (0.0715) _(0.0709)_
EMN		-0.0144 (0.0495) _(0.0485)_	0.0256 (0.0516) _(0.0500)_	0.0332 (0.0512) _(0.0504)_	0.0524 (0.0515) _(0.0513)_	-0.0285 (0.0551) _(0.0584)_	-0.0204 (0.0531) _(0.0569)_	-0.0250 (0.0552) _(0.0578)_	-0.1342 (0.0674)** _(0.0709)_*	-0.1698 (0.0490)*** _(0.0571)_***
EGE1		-0.0119 (0.0403) _(0.0411)_	-0.0319 (0.0394) _(0.0375)_	-0.0194 (0.0395) _(0.0380)_	-0.0181 (0.0391) _(0.0381)_	-0.0414 (0.0405) _(0.0433)_	-0.0438 (0.0392) _(0.0432)_	-0.0406 (0.0399) _(0.0441)_	0.0141 (0.0501) _(0.0552)_	-0.0302 (0.0328) _(0.0404)_
AGE				-0.0104 (0.0048)** _(0.0047)_**	-0.0116 (0.0048)** _(0.0045)_**	-0.0108 (0.0049)** _(0.0045)_**	-0.0070 (0.0048) _(0.0043)_	-0.0102 (0.0050)** _(0.0047)_**	-0.0101 (0.0059)* _(0.0058)_*	-0.0069 (0.0046) _(0.0046)_
LFSTOCK					-0.3462 (0.1601)** _(0.1767)_*					
ECACRA						-0.0038 (0.0027) _(0.0030)_				
UNEM							0.6455 (0.2501)** _(0.2144)_***	0.0605 (0.1989) _(0.1904)_	0.6148 (0.3592)* _(0.3993)_	0.2864 (0.2140) _(0.2109)_
INACTIVE								-0.0061 (0.0023)*** _(0.0026)_**		
ECACRF							-0.0057 (0.0022)** _(0.0025)_**		-0.0049 (0.0028)* _(0.0031)_	-0.0048 (0.0019)** _(0.0021)_**
YR98*URBANDPAV									0.0587 (0.0206)*** _(0.0191)_***	
YR00*URBANDPAV									0.0046 (0.0251) _(0.0237)_	
YR98*LAT										0.0007 (0.0001)*** _(0.0001)_***
YR00*LAT										-0.0004 (0.0002)* _(0.0002)_**
CONSTANT	0.1140 (0.0262)*** _(0.0321)_***	0.1201 (0.0668)* _(0.0668)_*	0.2414 (0.0872)*** _(0.0835)_***	0.6340 (0.2021)*** _(0.1926)_***	0.8441 (0.2225)*** _(0.2135)_***	0.8963 (0.2734)*** _(0.2821)_***	0.7269 (0.2302)*** _(0.2273)_***	0.8957 (0.2263)*** _(0.2217)_***	0.5724 (0.3246)* _(0.3692)_	0.4869 (0.2440)** _(0.2538)_*
ADJ R-SQ	0.0632	0.0005	0.0748	0.0967	0.1184	0.1023	0.1638	0.1313	0.2485	0.4216
OBS.	306	298	298	298	298	270	270	270	163	270

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. _(*), (**)_ and _(***)_ denote the significance of the White (1980) estimator.

Appendix A7.2: FEs: Dependent Variable is GGR2I and Independent Variables are NMN_LN, NGE1, EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(10)	(11)
NMN_LN	-0.0395 (0.0212)* *(0.0229)**		-0.0637 (0.0276)** *(0.0280)***	-0.0311 (0.0293) *(0.0304)*	-0.0277 (0.0288) *(0.0293)*	-0.0182 (0.0312) *(0.0339)*	-0.0111 (0.0302) *(0.0312)*	-0.0105 (0.0310) *(0.0323)*	0.1164 (0.0437)*** *(0.0453)***	0.1176 (0.0298)*** *(0.0352)****
NGE1	0.0890 (0.0735) *(0.0666)*		0.0941 (0.0760) *(0.0672)*	0.0731 (0.0750) *(0.0690)*	0.0404 (0.0746) *(0.0745)*	0.0191 (0.0844) *(0.0860)*	-0.0299 (0.0817) *(0.0823)*	0.0046 (0.0826) *(0.0869)*	-0.0208 (0.1058) *(0.1059)*	-0.0826 (0.0682) *(0.0732)*
EMN		-0.0144 (0.0495) *(0.0485)*	0.0144 (0.0518) *(0.0504)*	0.0298 (0.0511) *(0.0507)*	0.0562 (0.0511) *(0.0514)*	-0.0332 (0.0540) *(0.0567)*	-0.0186 (0.0520) *(0.0549)*	-0.0234 (0.0544) *(0.0562)*	-0.1448 (0.0670)** *(0.0702)***	-0.1678 (0.0481)*** *(0.0550)****
EGE1		-0.0119 (0.0403) *(0.0411)*	-0.0239 (0.0403) *(0.0404)*	-0.0092 (0.0398) *(0.0400)*	-0.0127 (0.0392) *(0.0396)*	-0.0381 (0.0407) *(0.0447)*	-0.0433 (0.0391) *(0.0439)*	-0.0382 (0.0399) *(0.0452)*	0.0128 (0.0490) *(0.0539)*	-0.0276 (0.0326) *(0.0389)*
AGE				-0.0134 (0.0047)*** *(0.0043)****	-0.0134 (0.0046)*** *(0.0041)****	-0.0127 (0.0046)*** *(0.0041)****	-0.0070 (0.0047) *(0.0041)**	-0.0112 (0.0047)** *(0.0042)****	-0.0099 (0.0058)* *(0.0056)**	-0.0071 (0.0045) *(0.0047)*
LFSTOCK					-0.4256 (0.1513)*** *(0.1651)***					
ECACRA						-0.0049 (0.0026)* *(0.0028)**				
UNEM							0.6643 (0.2432)*** *(0.2129)****		0.5548 (0.3560) *(0.4039)*	0.2162 (0.2109) *(0.2086)*
INACTIVE								0.0931 (0.1967) *(0.1827)*		
ECACRF							-0.0059 (0.0021)*** *(0.0023)***	-0.0066 (0.0022)*** *(0.0024)****	-0.0049 (0.0028)* *(0.0030)*	-0.0041 (0.0019)** *(0.0020)***
YR98*URB ANDPAV									0.0648 (0.0207)*** *(0.0190)****	
YR00*URB ANDPAV									0.0054 (0.0234) *(0.0214)*	
YR98*LAT										0.0008 (0.0001)*** *(0.0001)****
YR00*LAT										-0.0003 (0.0002) *(0.0002)*
CONSTAN T	0.1845 (0.0573)*** *(0.0613)****	0.1201 (0.0668)* *(0.0668)**	0.2551 (0.0912)*** *(0.0917)****	0.7607 (0.1967)*** *(0.1828)****	0.9659 (0.2065)*** *(0.1869)****	1.0559 (0.2502)*** *(0.2396)****	0.7422 (0.2191)*** *(0.2041)****	0.9584 (0.2109)*** *(0.1936)****	0.5476 (0.3200)* *(0.3596)*	0.4540 (0.2431)* *(0.2580)**
ADJ R-SQ	0.0220	0.0005	0.0332	0.0736	0.1106	0.0940	0.1647	0.1290	0.2616	0.4290
OBS.	306	298	298	298	298	270	270	270	163	270

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator.

Appendix A7.3: REs: Dependent Variable is GGR2I and Independent Variables are IMN_LN, IGE1, EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IMN_LN	-0.0144 (0.0089) (0.0108)		0.0003 (0.0116) (0.0154)	0.0001 (0.0116) (0.0155)	0.0008 (0.0121) (0.0160)	0.0002 (0.0123) (0.0171)	-0.0037 (0.0139) (0.0183)
IGE1	0.0464 (0.0249)* (0.0273)*		0.0638 (0.0239)*** (0.0256)**	0.0623 (0.0247)** (0.0262)**	0.0553 (0.0295)* (0.0284)*	0.0996 (0.0324)*** (0.0305)***	0.0916 (0.0362)** (0.0342)***
EMN		0.0540 (0.0175)*** (0.0162)***	0.0780 (0.0198)*** (0.0201)***	0.0773 (0.0201)*** (0.0205)***	0.0800 (0.0214)*** (0.0218)***	0.0543 (0.0237)** (0.0255)**	0.0611 (0.0242)** (0.0253)**
EGE1		0.0623 (0.0116)*** (0.0120)***	0.0636 (0.0124)*** (0.0124)***	0.0636 (0.0125)*** (0.0127)***	0.0655 (0.0138)*** (0.0139)***	0.0579 (0.0150)*** (0.0170)***	0.0589 (0.0161)*** (0.0178)***
AGE				-0.0003 (0.0014) (0.0014)	-0.0005 (0.0014) (0.0014)	0.0001 (0.0015) (0.0015)	-0.0006 (0.0015) (0.0016)
LFSTOCK					-0.0244 (0.0591) (0.0560)		
ECACRA						0.0015 (0.0007)** (0.0008)*	
UNEM							-0.0627 (0.1081) (0.0955)
INACTIVE							
ECACRF							0.0007 (0.0006) (0.0008)
ROAD (fixed)							
RAIL (fixed)							
URBANDPAV (fixed)							
LAT (fixed)							
DWSLIB							
DWSCORP							
DWSRES							
DRLCATH							
DRLORTH							
DRLANGL							
DFNC							
DFSC							
CONSTANT	0.1156 (0.0285)*** (0.0344)***	0.0108 (0.0217) (0.0210)	-0.0335 (0.0406) (0.0448)	-0.0170 (0.0775) (0.0733)	0.0026 (0.0873) (0.0771)	-0.1152 (0.0947) (0.0867)	-0.0214 (0.0991) (0.0985)
OBS.	306	298	298	298	298	270	270

Note: (*), (**), and (***) indicate significance at the 10%, 5% and 1% level, respectively. (*), (**) and (***) denote the significance of the White (1980) estimator.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
IMN_LN	-0.0020 (0.0122) (0.0177)	0.0390 (0.0244) (0.0386)	-0.0187 (0.0213) (0.0213)	-0.0059 (0.0145) (0.0183)	-0.0205 (0.0169) (0.0199)	0.0064 (0.0154) (0.0213)	-0.0091 (0.0171) (0.0211)
IGE1	0.0714 (0.0360)** (0.0338)**	0.1384 (0.0474)*** (0.0613)**	0.1333 (0.0510)*** (0.0456)***	0.1002 (0.0405)** (0.0418)**	0.1279 (0.0368)*** (0.0331)***	0.0872 (0.0380)** (0.0340)**	0.0984 (0.0389)** (0.0341)***
EMN	0.0714 (0.0237)*** (0.0244)***	0.0630 (0.0479) (0.0605)	0.0474 (0.0308) (0.0339)	0.0611 (0.0243)** (0.0254)**	0.0226 (0.0284) (0.0309)	0.0255 (0.0294) (0.0304)	0.0594 (0.0256)** (0.0259)**
EGE1	0.0613 (0.0146)*** (0.0165)***	0.0410 (0.0245)* (0.0225)*	0.0350 (0.0210)* (0.0235)	0.0597 (0.0163)*** (0.0180)***	0.0362 (0.0177)** (0.0212)*	0.0460 (0.0191)** (0.0224)**	0.0572 (0.0169)*** (0.0186)***
AGE	-0.0027 (0.0018) (0.0015)*		-0.0004 (0.0020) (0.0022)	-0.0006 (0.0016) (0.0016)	0.0008 (0.0016) (0.0016)	-0.0003 (0.0017) (0.0017)	-0.0005 (0.0016) (0.0016)
LFSTOCK							
ECACRA							
UNEM	0.2319 (0.0929)** (0.0814)***		-0.0749 (0.1849) (0.1654)	-0.0624 (0.1085) (0.0961)	0.0039 (0.1182) (0.1147)	0.0816 (0.1204) (0.1085)	-0.0710 (0.1149) (0.0999)
INACTIVE	0.0016 (0.0007)** (0.0008)**						
ECACRF			0.0019 (0.0008)** (0.0009)**	0.0007 (0.0006) (0.0008)	0.0004 (0.0007) (0.0008)	0.0009 (0.0006) (0.0008)	0.0007 (0.0007) (0.0008)
ROAD (fixed)		0.2324 (0.4618) (0.4617)					
RAIL (fixed)		-0.4222 (0.2435)* (0.2475)*					
URBANDPAV (fixed)			0.0319 (0.0186)* (0.0183)*				
LAT (fixed)				0.0004 (0.0009) (0.0010)			
DWSLIB					0.0093 (0.0154) (0.0203)		
DWSCORP					-0.0164 (0.0145) (0.0182)		
DWSRES					-0.0437 (0.0226)* (0.0246)*		
DRLCATH						0.0066 (0.0100) (0.0081)	
DRLORTH						0.0292 (0.0191) (0.0166)*	
DRLANGL						0.0228 (0.0106)** (0.0117)*	
DFNC							-0.0007 (0.0148) (0.0190)
DFSC							-0.0075 (0.0144) (0.0152)
CONSTANT	-0.0772 (0.0866) (0.0806)	-0.1030 (0.0814) (0.1024)	-0.0534 (0.1311) (0.1278)	-0.0421 (0.1090) (0.1137)	0.0111 (0.1055) (0.1006)	-0.0505 (0.1003) (0.0948)	-0.0117 (0.1048) (0.0993)
OBS.	270	114	163	270	270	270	270

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. (*), (**) and (***) denote the significance of the White (1980) estimator.

Appendix A7.4: REs: Dependent Variable is GGR2I and Independent Variables are NMN_LN, NGE1, EMN and EGE1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NMN_LN	-0.0149 (0.0081)* *(0.0099)*		0.0006 (0.0117) *(0.0157)*	0.0000 (0.0118) *(0.0158)*	0.0016 (0.0120) *(0.0161)*	-0.0004 (0.0127) *(0.0175)*	-0.0004 (0.0139) *(0.0180)*
NGE1	0.1395 (0.0364)*** *(0.0374)****		0.0979 (0.0378)** *(0.0410)***	0.0969 (0.0381)** *(0.0412)***	0.0842 (0.0392)** *(0.0414)***	0.1074 (0.0423)** *(0.0438)***	0.1010 (0.0444)** *(0.0461)***
EMN		0.0540 (0.0175)*** *(0.0162)****	0.0527 (0.0177)*** *(0.0181)****	0.0522 (0.0179)*** *(0.0184)****	0.0694 (0.0215)*** *(0.0218)****	0.0429 (0.0243)* *(0.0259)**	0.0525 (0.0250)** *(0.0258)***
EGE1		0.0623 (0.0116)*** *(0.0120)****	0.0526 (0.0133)*** *(0.0143)****	0.0531 (0.0135)*** *(0.0148)****	0.0602 (0.0145)*** *(0.0155)****	0.0556 (0.0159)*** *(0.0185)****	0.0590 (0.0167)*** *(0.0190)****
AGE				-0.0012 (0.0013) *(0.0013)*	-0.0014 (0.0013) *(0.0013)*	-0.0013 (0.0014) *(0.0014)*	-0.0013 (0.0016) *(0.0016)*
LFSTOCK					-0.0697 (0.0468) *(0.0458)*		
ECACRA						0.0004 (0.0006) *(0.0007)*	
UNEM							0.0169 (0.1066) *(0.0967)*
INACTIVE							
ECACRF							0.0000 (0.0005) *(0.0006)*
ROAD (fixed)							
RAIL (fixed)							
URBANDPAV (fixed)							
LAT (fixed)							
DWSLIB							
DWSCORP							
DWSRES							
DRLCATH							
DRLORTH							
DRLANGL							
DFNC							
DFSC							
CONSTANT	0.1078 (0.0262)*** *(0.0315)****	0.0108 (0.0217) *(0.0210)*	-0.0043 (0.0396) *(0.0435)*	0.0531 (0.0717) *(0.0633)*	0.0786 (0.0737) *(0.0627)*	0.0374 (0.0803) *(0.0693)*	0.0516 (0.0941) *(0.0921)*
OBS.	306	298	298	298	298	270	270

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*), (**)* and *(***)* denote the significance of the White (1980) estimator.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
NMN_LN	-0.0043 (0.0126) *(0.0182)*	0.0262 (0.0229) *(0.0350)*	-0.0136 (0.0215) *(0.0223)*	0.0000 (0.0146) *(0.0179)*	-0.0107 (0.0166) *(0.0188)*	0.0095 (0.0152) *(0.0205)*	0.0008 (0.0166) *(0.0197)*
NGE1	0.0827 (0.0428)* *(0.0434)**	0.1782 (0.0632)*** *(0.0693)***	0.1603 (0.0587)*** *(0.0576)****	0.0996 (0.0473)** *(0.0537)**	0.1261 (0.0461)*** *(0.0467)****	0.0753 (0.0470) *(0.0504)*	0.1036 (0.0479)** *(0.0462)***
EMN	0.0652 (0.0243)*** *(0.0246)****	0.0152 (0.0446) *(0.0606)*	0.0451 (0.0313) *(0.0348)*	0.0526 (0.0250)** *(0.0260)***	0.0174 (0.0290) *(0.0321)*	0.0251 (0.0297) *(0.0315)*	0.0555 (0.0261)** *(0.0263)***
EGE1	0.0570 (0.0155)*** *(0.0180)****	0.0116 (0.0250) *(0.0219)*	0.0389 (0.0218)* *(0.0262)*	0.0589 (0.0168)*** *(0.0189)****	0.0388 (0.0184)** *(0.0231)**	0.0506 (0.0195)** *(0.0244)***	0.0605 (0.0171)*** *(0.0193)****
AGE	-0.0036 (0.0017)** *(0.0015)***		-0.0015 (0.0021) *(0.0023)*	-0.0013 (0.0016) *(0.0016)*	-0.0005 (0.0016) *(0.0016)*	-0.0010 (0.0016) *(0.0017)*	-0.0015 (0.0016) *(0.0016)*
LFSTOCK							
ECACRA							
UNEM			0.1206 (0.1833) *(0.1627)*	0.0156 (0.1074) *(0.0990)*	0.1048 (0.1151) *(0.1117)*	0.1333 (0.1160) *(0.1043)*	0.0076 (0.1104) *(0.0974)*
INACTIVE	0.2519 (0.0927)*** *(0.0832)****						
ECACRF	0.0011 (0.0006)* *(0.0006)**		0.0007 (0.0008) *(0.0008)*	0.0000 (0.0006) *(0.0006)*	-0.0007 (0.0007) *(0.0007)*	0.0003 (0.0005) *(0.0006)*	-0.0001 (0.0007) *(0.0008)*
ROAD (fixed)		0.5628 (0.4515) *(0.4664)*					
RAIL (fixed)		-0.4215 (0.2413)* *(0.2374)**					
URBANDPAV (fixed)			0.0224 (0.0191) *(0.0185)*				
LAT (fixed)				-0.0001 (0.0009) *(0.0010)*			
DWSLIB					0.0021 (0.0165) *(0.0210)*		
DWSCORP					-0.0242 (0.0157) *(0.0192)*		
DWSRES					-0.0395 (0.0239)* *(0.0263)*		
DRLCATH						0.0079 (0.0101) *(0.0083)*	
DRLORTH						0.0344 (0.0195)* *(0.0174)***	
DRLANGL						0.0212 (0.0108)** *(0.0120)**	
DFNC							0.0054 (0.0157) *(0.0195)*
DFSC							0.0013 (0.0137) *(0.0139)*
CONSTANT	0.0055 (0.0779) *(0.0717)*	-0.0154 (0.0697) *(0.0841)*	0.0554 (0.1278) *(0.1270)*	0.0535 (0.0972) *(0.0965)*	0.1300 (0.1082) *(0.1048)*	0.0164 (0.0960) *(0.0901)*	0.0552 (0.1049) *(0.0992)*
OBS.	270	114	163	270	270	270	270

Note: (*), (**) and (***) indicate significance at the 10%, 5% and 1% level, respectively. *(*)*, *(**)* and *(***)* denote the significance of the White (1980) estimator.

Appendix A7.5: OLS, FEs and REs: Dependent Variable is GGR2I and Independent Variables are IMN_LN, IGE1, AMN and AGE1

	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_LN	-0.0218 (0.0103)** (0.0121)*	-0.0050 (0.0226) (0.0246)	-0.0205 (0.0106)* (0.0124)*	-0.0252 (0.0105)** (0.0129)*	0.0096 (0.0248) (0.0286)	-0.0239 (0.0109)** (0.0134)*	-0.0278 (0.0105)*** (0.0126)**	-0.0034 (0.0247) (0.0289)	-0.0276 (0.0108)** (0.0129)**	-0.0247 (0.0111)** (0.0138)*	0.0112 (0.0252) (0.0280)	-0.0243 (0.0114)** (0.0142)*
IGE1	0.0278 (0.0248) (0.0247)	0.1606 (0.0688)** (0.0605)***	0.0315 (0.0262) (0.0259)	0.0535 (0.0303)* (0.0282)*	0.1296 (0.0720)* (0.0665)*	0.0541 (0.0317)* (0.0292)*	0.0891 (0.0307)*** (0.0295)***	0.0932 (0.0833) (0.0771)	0.0886 (0.0316)*** (0.0300)***	0.1040 (0.0335)*** (0.0309)***	0.0338 (0.0851) (0.0804)	0.1018 (0.0348)*** (0.0316)***
AMN	-0.0028 (0.0014)** (0.0013)**	-0.0002 (0.0057) (0.0045)	-0.0029 (0.0015)* (0.0014)**	-0.0024 (0.0014)* (0.0014)*	0.0003 (0.0057) (0.0045)	-0.0025 (0.0015)* (0.0015)*	-0.0025 (0.0014)* (0.0014)*	-0.0012 (0.0057) (0.0045)	-0.0025 (0.0014)* (0.0015)*	-0.0035 (0.0015)** (0.0016)**	0.0006 (0.0057) (0.0046)	-0.0036 (0.0016)** (0.0017)**
AGE1	-0.4317 (0.1845)** (0.2038)**	-0.0554 (0.4859) (0.5464)	-0.4138 (0.1945)** (0.2180)*	-0.4599 (0.1851)** (0.2108)**	-0.0645 (0.4845) (0.5477)	-0.4418 (0.1948)** (0.2244)**	-0.3523 (0.1903)* (0.2178)	0.2460 (0.5072) (0.5328)	-0.3486 (0.1960)* (0.2265)	-0.3134 (0.1927) (0.2171)	0.2211 (0.5021) (0.5651)	-0.3085 (0.2001) (0.2278)
AGE	0.0011 (0.0014) (0.0013)	-0.0085 (0.0047)* (0.0047)*	0.0009 (0.0015) (0.0014)	0.0016 (0.0014) (0.0013)	-0.0091 (0.0047)* (0.0046)*	0.0014 (0.0015) (0.0014)	0.0021 (0.0014) (0.0013)	-0.0110 (0.0048)** (0.0047)**	0.0019 (0.0015) (0.0014)	0.0018 (0.0015) (0.0015)	-0.0085 (0.0048)* (0.0047)*	0.0017 (0.0015) (0.0016)
LFSTOCK				0.0776 (0.0525) (0.0539)	-0.2044 (0.1456) (0.1699)	0.0705 (0.0555) (0.0570)						
ECACRA							0.0027 (0.0006)*** (0.0006)***	-0.0027 (0.0026) (0.0028)	0.0027 (0.0006)*** (0.0007)***			
UNEM										0.0903 (0.1056) (0.1046)	0.4700 (0.2386)* (0.2192)**	0.1034 (0.1094) (0.1082)
INACTIVE												
ECACRF										0.0024 (0.0006)*** (0.0005)***	-0.0033 (0.0022) (0.0024)	0.0024 (0.0006)*** (0.0006)***
ROAD (fixed)												
RAIL (fixed)												
URBANDPAV (fixed)												
ADJ R-SQ	0.1505	0.0694		0.1544	0.0804		0.2269	0.0867		0.2235	0.1194	
OBS.	263			263			237			237		
LM TEST (p-value)	4.70 (0.0302)			3.76 (0.0524)			1.76 (0.1852)			2.12 (0.1452)		
HAUSMAN TEST (p-value)	11.17 (0.0481)			14.62 (0.0235)			14.07 (0.0288)			19.32 (0.0072)		

	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_LN	-0.0259 (0.0106)** (0.0124)**	0.0035 (0.0260) (0.0306)	-0.0259 (0.0108)** (0.0127)**	-0.0216 (0.0297) (0.0363)		-0.0216 (0.0297) (0.0363)	-0.0436 (0.0157)*** (0.0190)**	0.0337 (0.0455) (0.0469)	-0.0415 (0.0163)** (0.0197)**	-0.0241 (0.0129)* (0.0145)*	0.0473 (0.0339) (0.0365)	-0.0242 (0.0132)* (0.0148)
IGE1	0.0936 (0.0341)*** (0.0310)***	0.0732 (0.0854) (0.0816)	0.0931 (0.0349)*** (0.0315)***	0.0510 (0.0518) (0.0619)		0.0510 (0.0518) (0.0619)	0.1559 (0.0467)*** (0.0409)***	0.0628 (0.1183) (0.1089)	0.1540 (0.0499)*** (0.0430)***	0.1023 (0.0386)*** (0.0400)**	-0.0317 (0.0792) (0.0732)	0.1013 (0.0400)** (0.0405)**
AMN	-0.0026 (0.0014)* (0.0014)*	-0.0004 (0.0057) (0.0045)	-0.0026 (0.0014)* (0.0014)*	0.0074 (0.0047) (0.0052)		0.0074 (0.0047) (0.0052)	0.0054 (0.0038) (0.0042)	0.0105 (0.0163) (0.0196)	0.0049 (0.0041) (0.0045)	-0.0035 (0.0015)** (0.0016)**	0.0044 (0.0067) (0.0061)	-0.0037 (0.0016)** (0.0017)**
AGE1	-0.2668 (0.1946) (0.2125)	0.3002 (0.5087) (0.5474)	-0.2658 (0.1995) (0.2200)	-0.7194 (0.2887)** (0.2305)***		-0.7194 (0.2887)** (0.2305)***	-0.5597 (0.2369)** (0.2908)*	-0.1437 (0.6158) (0.9716)	-0.5328 (0.2549)** (0.3165)*	-0.3177 (0.1991) (0.2254)	-0.0930 (0.4695) (0.7002)	-0.3091 (0.2071) (0.2366)
AGE	-0.0003 (0.0017) (0.0015)	-0.0107 (0.0050)** (0.0050)**	-0.0003 (0.0018) (0.0016)				0.0004 (0.0019) (0.0021)	-0.0068 (0.0060) (0.0057)	0.0003 (0.0021) (0.0022)	0.0018 (0.0015) (0.0015)	-0.0034 (0.0050) (0.0052)	0.0016 (0.0015) (0.0016)
LFSTOCK												
ECACRA												
UNEM							-0.2347 (0.1752) (0.1728)	0.6726 (0.3724) (0.4076)*	-0.1892 (0.1886) (0.1865)	0.0908 (0.1059) (0.1046)	0.4016 (0.2186)* (0.2224)*	0.1042 (0.1100) (0.1083)
INACTIVE	0.1443 (0.0874) (0.0833)*	0.0309 (0.1856) (0.1961)	0.1401 (0.0894) (0.0855)									
ECACRF	0.0029 (0.0007)*** (0.0006)***	-0.0036 (0.0023) (0.0025)	0.0028 (0.0007)*** (0.0006)***				0.0020 (0.0007)*** (0.0007)***	-0.0039 (0.0031) (0.0034)	0.0020 (0.0008)** (0.0008)***	0.0024 (0.0006)*** (0.0005)***	-0.0028 (0.0021) (0.0022)	0.0024 (0.0006)*** (0.0006)***
ROAD (fixed)				0.3140 (0.4918) (0.4877)		0.3140 (0.4918) (0.4877)						
RAIL (fixed)				-0.5725 (0.2616)** (0.2776)**		-0.5725 (0.2616)** (0.2776)**						
URBANDPAV (fixed)							0.0389 (0.0162)** (0.0163)**		0.0388 (0.0180)** (0.0179)**			
YR98*URBANDPAV								0.0187 (0.0161) (0.0167)				
YR00*URBANDPAV								-0.0118 (0.0254) (0.0255)				
LAT (fixed)										-0.0001 (0.0009) (0.0012)		0.0000 (0.0010) (0.0012)
YR98*LAT											0.0003 (0.0002)* (0.0002)**	
YR00*LAT											-0.0004 (0.0003) (0.0002)*	
ADJ R-SQ	0.2302	0.0960		0.1770			0.1610	0.1927		0.2201	0.2801	
OBS.	237			83			163			237		
LM TEST (p-value)	1.30 (0.2546)			0.53 (0.4666)			0.16 (0.6873)			2.10 (0.1469)		
HAUSMAN TEST (p-value)	16.80 (0.0187)											

	REGRESSION 9			REGRESSION 10			REGRESSION 11			REGRESSION 12		
	(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_LN	-0.0402 (0.0129)*** *(0.0155)***		-0.0394 (0.0132)*** *(0.0158)***	-0.0299 (0.0122)** *(0.0152)**		-0.0290 (0.0125)** *(0.0156)**	-0.0146 (0.0125) *(0.0162)*		-0.0151 (0.0128) *(0.0164)*			
IGE1	0.1349 (0.0354)*** *(0.0349)****		0.1324 (0.0365)*** *(0.0355)****	0.1143 (0.0352)*** *(0.0309)****		0.1116 (0.0367)*** *(0.0320)****	0.0824 (0.0358)** *(0.0331)***		0.0826 (0.0368)** *(0.0337)***			
AMN	-0.0014 (0.0021) *(0.0021)*		-0.0016 (0.0021) *(0.0021)*	-0.0022 (0.0022) *(0.0020)*		-0.0024 (0.0022) *(0.0021)*	-0.0025 (0.0017) *(0.0021)*		-0.0027 (0.0017) *(0.0022)*			
AGE1	-0.0541 (0.2591) *(0.3059)*		-0.0493 (0.2664) *(0.3147)*	-0.3462 (0.2108) *(0.2544)*		-0.3321 (0.2190) *(0.2653)*	-0.5763 (0.2473)** *(0.3910)*		-0.5514 (0.2536)** *(0.3991)*			
AGE	0.0021 (0.0015) *(0.0015)*		0.0020 (0.0015) *(0.0016)*	0.0023 (0.0016) *(0.0016)*		0.0021 (0.0017) *(0.0017)*	0.0019 (0.0015) *(0.0016)*		0.0018 (0.0015) *(0.0017)*			
LFSTOCK												
ECACRA												
UNEM	0.0300 (0.1070) *(0.1113)*		0.0467 (0.1104) *(0.1144)*	0.0727 (0.1074) *(0.1044)*		0.0904 (0.1116) *(0.1087)*	0.1322 (0.1084) *(0.1146)*		0.1385 (0.1114) *(0.1175)*			
INACTIVE												
ECACRF	0.0017 (0.0006)*** *(0.0006)****		0.0017 (0.0006)*** *(0.0007)***	0.0022 (0.0006)*** *(0.0006)****		0.0022 (0.0006)*** *(0.0006)****	0.0026 (0.0006)*** *(0.0006)****		0.0026 (0.0006)*** *(0.0006)****			
ROAD												
RAIL												
URBANDPAV												
LAT												
DWSLIB	-0.0014 (0.0234) *(0.0272)*		-0.0020 (0.0246) *(0.0293)*									
DWSCORP	-0.0272 (0.0233) *(0.0277)*		-0.0271 (0.0245) *(0.0297)*									
DWSRES	-0.0454 (0.0320) *(0.0396)*		-0.0459 (0.0333) *(0.0416)*									
DRLCATH				0.0012 (0.0099) *(0.0079)*		0.0010 (0.0106) *(0.0085)*						
DRLORTH				-0.0071 (0.0172) *(0.0157)*		-0.0064 (0.0184) *(0.0167)*						
DRLANGL				0.0091 (0.0134) *(0.0121)*		0.0093 (0.0141) *(0.0127)*						
DFNC							-0.0038 (0.0230) *(0.0269)*		-0.0029 (0.0240) *(0.0286)*			
DFSC							0.0271 (0.0159)* *(0.0243)*		0.0251 (0.0164) *(0.0247)*			
ADJ R-SQ	0.2240			0.2173			0.2268					
OBS	237			237			237					
LM TEST (p-value)	0.87 (0.3519)			1.92 (0.1661)			1.08 (0.2994)					

Appendix A7.6: Standardised Coefficients: Dependent Variable is GGR2I

Independent Variables are IMN_LN, IGE1, EMN and EGE1

DEPENDENT VARIABLE: GGR2I											
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9	REGR. 10	REGR. 11
IMN_LN	-0.1290		0.0109	0.0107	0.0207	0.0262	-0.0126	-0.0002	0.3839	-0.1845	-0.0263
IGE1	0.1560		0.2175	0.2141	0.1940	0.3495	0.3326	0.2540	0.5163	0.4691	0.3542
EMN		0.3404	0.4913	0.4886	0.5049	0.3373	0.3828	0.4377	0.2840	0.3293	0.3821
EGE1		0.5933	0.6109	0.6123	0.6317	0.5290	0.5366	0.5525	0.3285	0.3182	0.5419
AGE				-0.0096	-0.0160	0.0214	-0.0083	-0.1037		-0.0020	-0.0065
LFSTOCK					-0.0362						
ECACRA						0.2194					
UNEM							-0.0584			-0.0839	-0.0581
INACTIVE								0.3207			
ECACRF							0.1569	0.3381		0.3775	0.1529
MOTOR									0.0676		
RAIL									-0.2735		
URBANDP AV (fixed)										0.1685	
LAT (fixed)											0.0459

Independent Variables are NMN_LN, NGE1, EMN and EGE1

DEPENDENT VARIABLE: GGR2I											
	REGR. 1	REGR. 2	REGR. 3	REGR. 4	REGR. 5	REGR. 6	REGR. 7	REGR. 8	REGR. 9	REGR. 10	REGR. 11
NMN_LN	-0.1084		0.0073	0.0079	0.0248	0.0204	0.0228	-0.0165	0.2128	-0.1183	0.0337
NGE1	0.2555		0.1676	0.1665	0.1459	0.1803	0.1700	0.1380	0.3404	0.2447	0.1601
EMN		0.3404	0.3317	0.3291	0.4362	0.2689	0.3318	0.4016	0.0707	0.3115	0.3353
EGE1		0.5933	0.5020	0.5116	0.5826	0.5158	0.5518	0.5203	0.0971	0.3550	0.5468
AGE				-0.0490	-0.0550	-0.0375	-0.0360	-0.1430		-0.0486	-0.0357
LFSTOCK					-0.1113						
ECACRA						0.0583					
UNEM							-0.0007			0.0607	-0.0045
INACTIVE								0.3500			
ECACRF							-0.0014	0.2258		0.1358	0.0145
MOTOR									0.1635		
RAIL									-0.2742		
URBANDP AV (fixed)										0.1180	
LAT (fixed)											-0.0429

Independent Variables are IMN_LN, IGE1, NMN_LN, NGE1, EMN and EGE1

DEPENDENT VARIABLE: GGR2I			
	REGR. 1	REGR. 2	REGR. 3
IMN_LN		-0.2228	
IGE1		0.0822	
NMN_LN			-0.1909
NGE1			0.2168
AMN	-0.3684	-0.1943	-0.1527
AGE1	0.0042	-0.1935	-0.1934

8 Chapter Eight. Conclusion

8.1 Introduction

As noted in the first chapter, the main objective of this thesis has been to analyse the impact of income and educational inequalities on regional economic growth. Because of the complexity of the issue and the relative absence of a coherent analytical background on which to base the empirical investigation, this analysis was divided into methodological steps. The first step dealt mainly with the association between income and educational distribution, while the second focused explicitly on the main research question, which was whether income and educational inequalities matter for growth. The main purpose of this chapter is to combine the conclusions from the previous chapters, to draw out a number of policy implications about the role of inequalities in regional economic growth, to discuss some potential limitations of the thesis and to suggest areas for further research.

The chapter is structured as follows. Section 8.2 answers the research questions in view of the findings and limitations of this study. Each answer will be presented separately. After the questions have been answered, Section 8.3 provides useful insights for the planning of regional policy in the EU. The conclusion, and this thesis, ends with a section on the issues proposed for further research.

8.2 Empirical Findings: A Short Answer to the Research Questions

In light of the empirical findings and the existing theoretical background, this section gives a brief answer to the research questions.

The main research question is the following.

Do income and educational inequalities matter for growth?

The focal point of this study has been to examine the impact of income and educational distribution on regional economic growth.

(1) Considering *the distribution of the education level completed*, the regression results indicate that, on the basis of existing levels of inequality in Europe, an increase in a region's level of income inequality (either for the population as a whole or for normally

working people) and educational one has a significant positive relationship with subsequent economic growth. This relationship indicates a *laissez-faire* regional economy, in which government intervention is minimal and inequality is fundamentally seen to be good for socioeconomic incentives (Mirrlees, 1971; Rebelo, 1991; Aghion et al., 1998). Educational inequality motivates and enables people to increase their investment in human capital in order to obtain higher educational qualifications, because they require qualifications that are not possessed to everyone so as to benefit from the higher returns to their skills. Income inequality enables people to acquire well-paid jobs, increasing competition in the labour market and, therefore, growth. Additionally, public policies (i.e. tax policies) aimed at reducing income inequality may not be strong enough to produce negative incentives. The results also coincide with the current belief that educational achievement has a positive relationship with economic growth. Education seems to be a critical factor in determining the productive capacity of the regional economy, and thus is one of the most powerful instruments for laying the basis for sustained growth (Hannum and Buchmann, 2005).

(2) Considering *the distribution of the age at which the highest education level was completed*, the results reveal negative coefficients on educational inequality and educational attainment, but they are very sensitive to the model specification. In this case, educational equality may encourage more members of society to increase their investment in human capital, thus stimulating growth. According to de la Fuente and Domenech (2006: 5), the 'wrong' sign of educational attainment has fuelled growing scepticism with regard to its role in the growth process.

No matter how income and educational inequality is measured, the empirical arguments do not favour a causal link between growth and changes in inequality levels. Moreover, the regression results indicate a convergence process across European regions, but this is very sensitive to the inclusion of control variables.

To sum up, both income and educational inequalities matter for regional economic growth. While the influence of income inequality is robust to the definition of income distribution, the impact of educational inequality is sensitive to the definition of educational distribution. This may have to do with the meaning of human capital, because a measure of age on completing the highest qualification includes any activity prior to that final qualification, some of which may contribute to building human capital and some not. Finally, the standardised coefficients show that the effect of income and educational inequalities on growth is more intensive than that of income per capita and educational attainment. As this study contributes to two different strands within the field of economic growth, the strand focused on inequality and growth outweighs the strand of average and growth in terms of its significance.

In order to come to the above conclusions, the research question was decomposed into a number of sub-questions, for which the main concluded points are as follows.

1. Are income inequalities associated with educational inequalities?

Educational attainment reflects non-monetary rewards, while income reflects monetary rewards. Nevertheless, income inequality is positively associated with educational inequality.

On the one hand, people with more education earn more money. Both degrees and personal characteristics (i.e. innate ability, psychological traits) matter for income variations. Firstly, the most-educated get the highest earnings because education directly increases workers' productivity and allows them to command higher earnings. Education also increases the social and job opportunities available to people. It is an instrument for a higher level of aspiration, leading people to be more informed and, therefore, gain specific traits which may increase productivity. Secondly, the most talented and high-ability people have a high level productivity, because they can function better with less knowledge than others do. In this case, education has no direct effect on wages because it acts as 'signal' (Spence, 1973, 1974). Education is seen as an elaborate device for detecting and labelling those who have skills (Champernowne and Cowell, 1998; Wolf, 2004). On this basis, a greater share of highly-educated workers may signal to employers that those with less education have a lower ability, which may also lead to a larger wage differential between highly-educated and low-educated workers, and thus to higher income inequality. Therefore, the greater the educational inequality, the greater the inequality in productivity — either due to qualifications or due to personal characteristics — and the greater the income inequality. The positive impact of educational inequality on income inequality may reflect the responsiveness of the EU labour market to differences in qualifications and skills.

On the other hand, although education is a key instrument in securing equal opportunities for people and for helping to improve their living standards (Wolf, 2002), rich people have more educational opportunities than the poor. An increase in income inequality may lead to a self-perpetuating poverty trap that may increase educational inequality (Checchi, 2000). Therefore, the higher the income inequality, the larger the population that is excluded from educational opportunities, and the higher the educational inequalities.

Income and educational inequalities seem to be mutually self-reinforcing processes. Human capital produces income, and vice versa. Income inequality is strongly related to educational inequality, but the scale of the effect is relatively small. Both income and human capital inequalities are likely to indicate inequalities in abilities, knowledge, skills, aspiration, socioeconomic chances, opportunities and so on.

To delve a little deeper, regardless the quality of institutions, two European forces behind the positive income-education relationship are tertiary education and individual abilities. First, primary and secondary education is compulsory and free in all European countries. *Ceteris paribus*, this gives poor people the 'same' educational opportunities as the rich, they then might use these to have the 'same' job chances so as to earn the 'same' wages and probably have the 'same' income. If primary and secondary education per se does not affect income distribution because it is provided to all people, it may be that it is individual abilities and certain psychological and personality traits (such as diligence) that employers reward and, thus, it is these factors that determine an individual's income. Moreover, people differ with regard to their potential skills and preferences. Thus, a person with a higher level of cognitive ability can work better than a person with otherwise the same level of education (Galor and Tsiddon, 1997b; Hassler and Mora, 2000). The former is more productive and is likely to have a larger income. Second, the European capital markets are not so perfect that anyone may borrow against their expected future earnings. The imperfect allocation of educational loans for tertiary education (since primary and secondary education is free and public) seems to reinforce the positive correlation between income and education. Otherwise, income and educational inequality, for example, could be negatively correlated or uncorrelated, because every individual would have access to the 'same' educational opportunities and chances. Hence, tertiary education might be a crucial factor under current credit market constraints. Tertiary education exerts an influence on the demand for and supply of skilled labour and, hence, on relative wages and incomes (Tinbergen, 1975).

Overall, tertiary education and individual abilities seem to be the most important factors underlying the income-education relationship. Although the European educational policy is to make tertiary education more affordable over time through grants, subsidised loans and other financial devices, this alone is insufficient to ensure that all people have access to the 'same' educational opportunities, because low individual abilities may restrict the option of higher educational attainment. Differences in tertiary educational attainment and in abilities probably explain a small part of the differences in income and human capital distribution, because most socioeconomic theories tend to have offsetting effects.

2. Are income and educational inequalities affected by common factors, such as population ageing, work access, unemployment and inactivity?

Both income and educational inequalities are affected by population ageing, work access, unemployment and inactivity (Table 8.1). The impact of population ageing on income inequalities is unclear. On the one hand, regions with a very young population may have lower rate of participation in the labour force, leading to high levels of income inequality for the population as a whole. Additionally, young people in work earn less in the labour market. On the other hand, an increasing number of elderly and retired people, whose income is lower than the mature working age cohort, may lead to a rise in income inequality among normally working people (Estudillo, 1997). The coefficient on population ageing for educational inequality models is positive, reflecting the fact that as people get older, the luck of educational opportunities diversifies the educational distribution (Motonishi, 2006). The effect of both proxies for work access on income and educational inequalities is negative. Higher access to work seems to lead to less inequality. While the impact of unemployment on inequality is positive, the impact of inactivity is negative. On the one hand, increases in unemployment aggravate the relative position of low-income and low-education groups, because marginal workers with the relatively low wages, skills and qualifications are at the bottom of the income and educational distribution and their jobs are at greater risk during an economic downturn. Forms of income support and benefits are not enough to offset the loss in income due to transitory unemployment. On the other hand, the higher the percentage of inactive young people, the lower the educational inequality in the long run, because more widespread access to education means that young people remain out of the labour market for longer, which means the increased occurrence of youth inactivity (Rodríguez-Pose, 2002). The coefficients on women's work access are negative and statistically significant for the most regressions. The impact of the increase in women's access to work has been to lessen the trend toward greater income and educational inequality caused by aspects of social change during the period of analysis. Additionally, increasing women's access to the labour market through more adequate childcare services, more flexible working conditions and more sharing of family responsibilities implies greater opportunities to engage in paid work. Finally, female participation in the labour force explains a major part of the variation in income and educational inequality.

Table 8.1: The Impact of Population Ageing, Work Access, Unemployment and Inactivity on Inequality

	dependent variable															
	income inequality for all people				income inequality for normally working people				inequality in education level completed				inequality in age at which the highest education level was completed			
independent variables	education level completed		age at which the highest education level was completed		education level completed		age at which the highest education level was completed		income for all people		income for normally working people		income for all people		income for normally working people	
	st.	dyn.	st.	dyn.	st.	dyn.	st.	dyn.	st.	dyn.	st.	dyn.	st.	dyn.	st.	dyn.
population ageing	-	n.s.	-	n.s.	n.s.	+	n.s.	+	+	+	+	+	+	n.s.	+	n.s.
work access (micro)	-	n.s.	-	n.s.					n.s.	n.s.	n.s.	n.s.	n.s.	-	n.s.	n.s.
work access (macro)	-	-	-	-					-	-	-	-	n.s.	n.s.	n.s.	n.s.
unemployment	+	+	+	n.s.					n.s.	n.s.	n.s.	n.s.	+	n.s.	+	n.s.
inactivity	n.s.	-	n.s.	n.s.					n.s.	-	n.s.	-	-	n.s.	-	n.s.
women's work access	-	-	-	-	-	-	-	-	-	-	-	-	n.s.	n.s.	n.s.	n.s.

Note: 'n.s.' means not statistically significant coefficient; st. denotes static models; and dyn. denotes dynamic models.

3. Does the exploratory analysis of income and educational inequalities suggest any form of spatial heterogeneity such as an urban-rural divide or an EU north-south divide?

Both the ESDA and the static regression models reveal two distinct patterns.

Firstly, income and educational inequalities have evolved differently in urban and rural areas. Urbanisation, as measured by the proportion of respondents who live in a densely populated area, is negatively associated with income inequality, but this is sensitive to the definition of income inequality. The coefficient on urbanisation is statistically significant when the dependent variable is the income inequality of the population as a whole and statistically insignificant the when dependent variable is the income inequality of normally working people. That sensitivity is likely to reflect the fact that it is more likely that all members of a household move to urban areas in search of better opportunities rather than only normally working people. The income inequality of the population as a whole is lower in agglomerated areas, which is as might be expected because considering that urbanisation is a measure of economic development (Kuznets, 1955) and most European regions are at an advanced stage of economic development, a greater metropolitan share should reduce income inequality. In terms of educational inequality, the urban-rural divide is statistically significant for both proxies but in a different direction. The impact of urbanisation on inequality in the age at which the highest education level was completed is negative, but its impact on inequality in the education level completed is, surprisingly, positive. This may be a reflection of the differences in human capital proxies. Highly-educated workers living in rural areas are likely to move to cities in order to achieve promotion and greater employment returns, while people who completed their education at an older age are more likely to move to rural areas. Nevertheless, the fact that data on urbanisation were available for only a few regions means that the results should be treated with a certain degree of caution.

Secondly, the ESDA on income and educational inequality has addressed the role of latitude as a major determinant of inequalities, highlighting the EU north-south divide, among other effects. Income and educational inequality is higher in the south than in the north. This finding is robust to the definition of income and human capital. The north-south divide in terms of inequality may reflect the differences in female participation in the labour market, in unemployment, in the provision of the welfare state and in family structure. The analytical concept in understanding the relationship between latitude and inequalities may not be a matter of the 'second' nature of geography alone, but also a matter of its 'first' nature, because latitude is a pure geographical variable. Adam Smith made a notable hypothesis that physical geography influences regional economic performance and, thus, inequalities. Considering that latitude serves as a good proxy for a region's climate, the results show that climatic variation may affect productivity and inequality.

Finally, the regression analysis also shows that the impact of both urbanisation and latitude on inequalities was higher in 2000 than in 1995.

4. What is the impact of institutional factors, such as welfare state, religion and family structure, on inequalities?

The regression results show that income and educational inequalities are lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures, such as the Swedish and Danish regions. This finding is robust to the definition of inequalities.

Firstly, in social-democratic welfare states, the state provision of income and services is higher, the benefits and taxes are mainly individually-based, there is support for women's participation in the labour market and public care services to families enable women to have both children and careers. These factors reduce inequalities. According to Orloff (1993), social-democratic regimes are 'egalitarian'. Inequality is higher in the 'residual' welfare states, because the share of national income devoted to social purposes is very low, the social benefits are meagre and cover only the minority of the population (Sainsbury, 1991).

Secondly, religion as an aspect of social life and culture shapes income and educational distributions. The basic channels through which religion may influence income and education are marriage and divorce, fertility, childrearing, attitudes towards work, family traditions and cultures, and the creation of public institutions such as blue laws and prohibition. Although the impact of these factors on inequalities across religious affiliations is complex, income and educational equalities are lower in Protestant societies because gender equality in terms of housework is actively pursued, since women are encouraged to participate full-time in the labour market. Additionally, Protestants and Catholics are strongest on individualistic beliefs, which locate the causes of low income and a lack of education in the individuals themselves. This motivates them to acquire higher qualifications and to participate fully in the labour market so as to get better jobs.

Thirdly, the concept of family structure developed in this study is linked to the household size. Income and educational inequalities are lower in Nordic countries because both husband and wife contribute to living expenses and both support the children. In contrast to this view, in Southern/Catholic societies the husband is expected to support the wife, who usually acts as a full-time homemaker. Women are the main care providers in these households. In these societies, the husband's wage must be large enough to support his wife and their children. This increases the intra-household income inequality. With regard to education, the larger the household size, the higher the intra-household educational inequality, as rich people have usually less children than poor ones do.

Finally, the impact of institutions on inequalities has some overlapping outcomes. For instance, conservative regimes are influenced by the social policy of the Catholic Church (Geist, 2005: 26) and religions which favour low levels of fertility decrease the household size.

5. Do population ageing, work access, unemployment and inactivity affect regional economic growth directly or indirectly through their impact on inequalities?

Population ageing, work access, unemployment and inactivity affect regional economic growth both directly and indirectly (Table 8.2). The findings indicate that population ageing is negatively associated with growth. This most probably reflects the fact that younger workers are more productive than older ones, because the former are the primary adopters and beneficiaries of new technologies, work more hours, are able to concentrate more on the job, are healthier and take fewer days off as sick leave. The impact of access to work on regional economic growth is positive. Greater access to work access may contribute to a competitive regional economic environment, promoting allocative efficiency, and thus enhancing economic growth (Azzoni and Silveira-Neto, 2005). However, women hold the majority of low-income jobs, have less continuous employment than men and do not receive the same job-related rewards. Hence, a higher level of female participation in the labour market may not only promote allocative efficiency, but also may stimulate export expansion and the export earnings which, in turn, may provide the resources to purchase sophisticated technologies that permit economies of scale and specialisation and, thus, growth (Seguino, 2000). Both effects are highlighted in the positive coefficient on women's access to work. The influence of unemployment and inactivity on growth is positive. High economic inactivity and unemployment may stimulate efficiency gains by causing less efficient firms to exit and by encouraging firms to adopt reorganising investments and innovative activities. Hence economic recessions may stimulate growth.

Table 8.2: The Impact of Population Ageing, Work Access, Unemployment and Inactivity on Regional Economic Growth

	dependent variable			
	regional economic growth			
independent variables	income for all people / education level completed	income for normally working people / education level completed	income for all people / age at which the highest education level was completed	income for normally working people / age at which the highest education level was completed
population ageing	n.s.	-	-	-
work access (micro)	n.s.	n.s.	n.s.	n.s.
work access (macro)	+	n.s.	n.s.	n.s.
unemployment	n.s.	n.s.	+	+
inactivity	+	+	n.s.	n.s.
women's work access	+	+	n.s.	n.s.

Note: 'n.s.' means not statistically significant coefficient.

6. Do urbanisation, geography and institutions shape growth patterns?

Urbanisation shapes not only inequality patterns, but also patterns of growth. The coefficient on urbanisation is positive and statistically significant in most regressions. Highly agglomerated regions seem to have low costs of innovation, infrastructure, information and transaction, and to foster and facilitate flows of local knowledge, ideas and innovations, the creation of dense social networks and the production of behavioural and cultural change, because they are full of technological and pecuniary externalities. Additionally, cities allow goods, ideas and people to come together for the purposes of exchange and production (Polese, 2005). This allows city-regions to reap the gains from trade, services and specialisation. In cities, people have face-to-face contact which is a fundamental condition of tacit knowledge spillovers. Hence, the higher the degree of urbanisation, the greater the technological, pecuniary and tacit knowledge externalities and the higher the regional economic growth rate as well. This study has not found latitude to be an important factor in accounting for differences in cross-regional growth rates. However, latitude may shape growth through its impact on income and educational inequalities. The growth-institutions relationship is not very clear, because most of the dummies are statistically insignificant. Nevertheless, the regression results seem to show that regional economic growth is lower in 'residual' countries than in social-democratic ones, higher in Anglican areas than in Protestant areas, and higher in southern Catholic regions than in Nordic countries.

The *main empirical results* from the analysis of these questions are summarised as follows.

1. Income inequality is positively associated with educational inequality.
2. Inequalities matter for regional economic growth.
3. Urbanisation shapes both inequalities and growth, while geography and institutions shape only inequalities.

8.3 Policy Implications

The analysis provides useful insights that may be vital in the planning of regional policy in the EU. In this section I combine the conclusions drawn from the various parts of the analysis and draw out a number of policy implications with regard to the role of regional economic policy. Generally speaking, European regional policy should seek a synergy in the achievement of both efficiency and equity. However, this may involve trade-offs in the extent to which the two goals can be attained. The pursuit of these goals is a matter of political choice (Wossmann and Schütz, 2006). Liberal societies may put more emphasis on efficiency, while the emphasis in social-democratic ones may be on equity.

(1) The goals of European educational policy are two-fold, encompassing both goals of efficient allocation and goals of equitable distribution. The goals of efficiency and equity are likely to be achieved at each level of formal education and are not trade-offs, since educational policies may advance both efficiency and equity in such a way that each complements the other. The concept of equity is more evasive because it has to do with scientific definitions of fairness and justice (Wossmann and Schütz, 2006). Inequality in educational attainment should be tolerated only if it is due to differences in individual levels of effort (i.e. studying), but not if it is due to circumstances which are beyond a person's control (i.e. gender and family background). Hence, a person's expected educational outcome should be a function only of his/her effort, but not of his/her circumstances (Wossmann and Schütz, 2006). If this is the case, then individual abilities, along with certain specific traits and qualities, are likely to play the most prominent role in the income-education relationship. The regression results highlight the fact that educational policies have an impact on welfare policies, because the lower the

educational inequality, the lower the income inequality. Taking into account the goals of European educational policy, regional policies should take into account the responsiveness of the EU labour market to differences in qualifications and skills. The pursuit of the goal of equitable educational distribution is likely to decrease inequality in productivity and, thus, inequality in income. If, for example, European educational policy aims to reduce the cost of studying (i.e. by providing free accommodation to poor students) and to provide free education for all students (without tuition fees) so that more of the population to have the opportunity to attain higher education, occupations that require high levels of education will not be beyond the reach of poor people. European citizens who live in poverty will have a means of escape, because the problems of access to education will be eased. This is likely to lead to lower income inequality. However, the pursuit of goal of equitable educational distribution, all other things being constant, is likely to lead in the long-run to inflation in the value of educational credentials which, in turn, is likely to reduce the wages of highly-educated workers. In this case, people would not have the incentive to acquire higher qualifications. Therefore, policies which improve access to education, provide a higher quality of education and, generally, increase educational attainment are likely to alleviate inequalities not only in education, but also in income.

(2) One key goal of European welfare policy is the equitable distribution of income. Policies of income redistribution from rich to poor may reduce educational inequalities, as rich people generally have more educational opportunities than the poor. Government intervention may improve regional economic performance, because sometimes markets do not allocate resources efficiently. The government usually taxes the rich by taxing the incomes of rich people or the goods that rich people buy.

(3) European regional policies should take into account that income and educational externalities spill over the barriers of regional economies. A decrease in inequality within a region might well be caused by a policy (i.e. tax policy) which decreased inequality within neighbouring regions. Common regional activities in neighbouring regions (i.e. public infrastructures) and common policies across neighbouring regions (i.e. Structural Funds) affect all regions, highlighting the spatial autocorrelation of inequalities. Welfare and educational policies should account for the spillover effects with adjoining regions. Trade, migration, infrastructure and technological policies may also lead to geographically dependent regions. Factors such as labour force mobility, capital mobility, technology and transportation costs may be particularly important,

because they directly affect regional interactions (Le Gallo et al., 2003). For instance, policies on investment in infrastructure may influence the distribution of income and education within a region by changing the competitive advantages of neighbouring regions. If, for example, policies favour factor mobility, public infrastructure investments in one location can draw production away from other locations or provide access to adjacent locations that were not not previously accessible (Abreu et al., 2004). The economic and educational environment surrounding a region seems to influence the economic and educational perspectives of that region. Hence policy-makers should take into consideration that space matters for inequalities. The microeconomic data patterns and anomalies also should be considered in regional policy, because the exploratory analysis illuminates not only spatial dependence, but also spatial heterogeneity. The probability of neighbouring economies sharing similar conditions in terms of urbanisation, institutions and latitude is relatively high. In other words, there are urban, institutional and geographical limits to the spread of externalities. Regional economies within a specific welfare state regime, for example, interact more with one another than with those outside the regime. The mechanisms which directly affect regional interactions are stronger between regions of the same welfare state category. This implies that welfare state policies, such as unemployment benefits, affect inequality patterns. Since inequality evolves differently across family structures and religious affiliations, fertility, family, social, pension and cultural policies may also affect patterns of inequality. Policy-makers should also consider the role of the EU north-south divide in terms of income and educational inequality. A poor southern region with high inequality surrounded by other poor regions with high inequality will probably stay in this state of development, whereas a poor northern region with high inequality surrounded by richer regions and low inequality has a greater probability of reaching a higher state of development. Hence, the prevalence of interregional income and educational externalities can create poverty trap, because the clusters of the poorest and highest inequality European regions in Southern Europe may create a great disadvantage for those regions. If regional policies aim to reduce inequalities, they should place more emphasis on the south than the north. Finally, regional policies concerning inequalities may illustrate the systematic differences between agglomerations and rural peripheral regions with respect to the distribution of income and education. Consequently, spatial autocorrelation and spatial heterogeneity are, indeed, unavoidable features for efficient and equitable European regional policies.

(4) Policy-makers should pay more attention to the within-region income and educational inequalities than to between-region and between-country inequalities so as to formulate effective policies, because the within-region component constitutes the major portion of the European inequality. Moreover, national economic policies, such as monetary policies, tax policies, trade reforms and educational policies and guidelines, which have a common effect on all regions within national borders, may have a greater impact on wages and education than purely regional policies, because the between-country component is more significant than the between-region one.

(5) Inequalities in income and education level completed are likely to increase growth, but the magnitude of their impact is small. Policy-makers, therefore, should take into account that inequality is strongly related to growth, but the scale of the effect is relatively small, and thus the effectiveness of a regional policy to increase growth through inequalities is likely to be low. Policy-makers also should bear in mind that the reverse effect seems not to be valid. The positive inequality-growth relationship highlights that regional policies involve a trade-off, by either advancing growth efficiency to the detriment of educational and income equity or by advancing equity to the detriment of efficiency. Regions necessarily have to choose between efficiency and equity. Policy attempts to achieve one or the other are likely to be both inefficient and inequitable. Nevertheless, equality in the age at which the highest education level was completed is likely to increase growth. In this case, there is a complementarity in the achievement of both efficiency and educational equity. However, the overall outcome may not be complementarity, but rather a trade-off, because the lower the inequality in age, the lower the income inequality (either for the population as a whole or for normally working people) and, therefore, the lower the growth.

(6) As income distribution is positively associated with educational distribution, the relationship between income distribution and regional economic growth may be governed by the relationship between educational distribution and growth (Galor and Tsiddon, 1997a: 95). Although public policies aimed at reducing income inequality are expected to reduce educational inequality as well, and policies aimed at reducing educational inequalities are expected to reduce income inequality as well, those policies may produce negative incentives for regional economic efficiency and, therefore, may harm economic growth. Increasing inequality does not emerge as a simple remedy for increasing growth.

(7) Geographical, institutional and urban policies may not affect regional economic growth, because it is randomly distributed across the EU. Nevertheless, those policies may indirectly affect economic growth through their impact on income and educational inequalities.

To sum up, the analysis highlights the significance of a combined regional policy perspective that would address other policies such as labour market policies, educational policies, social policies, institutional policies and immigration policies. The combined policy should determine joined-up policy solutions, which encompass both the goal of economic efficiency (high growth) and the goals of equitable income and educational distribution (low income and educational inequality). The extent to which each of these goals should be pursued is a matter of political choice.

8.4 Limitations and Further Research

There are some plausible reasons for inconclusive or ambiguous findings. These insights should serve to advance future research. It is important to synthesise these empirical results and their implications at greater length. Considerable light can be shed on the following issues by further analysis.

(1) The analysis of this thesis has some limitations which to a large extent large result from *the availability and quality of the data.* The fact that data on only a limited time period were available means that the results should be interpreted with some caution. Longer time-series will reinforce the analysis. A potential limitation of the 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 (Nielsen and Alderson, 1997). Regions do not encompass as wide a range of variation in income and educational distribution, in 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 the distributional process (Nielsen and Alderson, 1997). Thus, the administrative boundaries used to organise the data series do not coincide perfectly with the actual boundaries, introducing nuisance spatial autocorrelation into data (Anselin and Rey, 1991). Finally, it would be valuable to refine the results on regional economic growth by considering data spanning longer periods. In terms of the quality of data, the fact that people are classified into just three categories with respect to the education level completed is a limitation.

(2) 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 the results to inequality indices* would reinforce the analysis. Nevertheless, one would expect the results to be expected robust to the inequality indices, because the analysis has demonstrated that the correlation among indices is very high, except for the squared coefficient of variation.

(3) The analysis shows that income distribution and educational distribution evolve jointly. Not only do income inequalities affect educational inequalities, but educational inequalities also affect income inequalities. This is an issue of *endogeneity*. The pattern of correlations between income and human capital raises the problem of difficulties in disentangling cause and effect. It is not clear in which direction the causal relationship runs. Thus, problems of simultaneity and causality are likely to abound. How income and human capital distributions are jointly determined is not well understood. The nature of the causal link is a subject of further research.

(4) The dynamic models were estimated using Arellano and Bond's (1991) estimator, which treats the dynamic model as a system of equations, one for each time period. This estimator is called the 'difference GMM' (GMM-DIF). One problem with the GMM-DIF estimator is that lagged levels are often poor instruments for first differences, especially for variables that are close to a random walk (Roodman, 2005). Arellano and Bover (1995) and Blundell and Bond (1998) show that the efficiency of the GMM-DIF estimator may be improved by using an extended system GMM estimator that uses not only lagged levels of the instruments for equations in first differences, but also lagged differences as instruments for equations in levels (Roodman, 2005). This estimator is called the '*system GMM*' (GMM-SYS). Hence, another suggestion for further research is that dynamic models might also be estimated by GMM-SYS.

(5) The arguments summarised above are tested empirically by estimating the reduced-form equation. The determinants of income and educational inequalities and the impact of those inequalities on regional economic growth are explored by estimating static and dynamic reduced-form equations. If, however, a significant coefficient estimate is obtained for the reduced-form equation, it is not obvious which of the structural mechanisms are responsible for this result. This could be tested empirically by estimating a *system of equations*. This is a step for further research.

(6) Income and educational inequalities have evolved differently in urban and rural areas, in northern and southern areas and across institutional categories (across welfare states, religious affiliations and family structures). A next step is to investigate whether these *alternate paths* are due to different responses to changes in population ageing, work access, unemployment and inactivity. However, this analysis requires more cross-sectional observations.

(7) As has been mentioned earlier, the proxies presented for educational attainment are measured in terms of the input of formal education, without considering the output of knowledge, skills and competences embodied in individuals (Sianesi and Van Reenen, 2003). This is a limitation of this study. Moreover, the regression results for growth equations are non-robust to the definition of human capital, since inequality in the education level completed is positively associated with growth, while inequality in the age at which the highest education level was completed negatively affects growth. This sensitivity may reflect the *differences in educational attainment concepts*. The main difference is that a measure of the age at which an individual acquired their highest qualification includes any activity prior to that final qualification, some of which may have contributed to building human capital and some not. Considerable light can be shed on these issues by further analysis of the ways that the growth results are sensitive to the definition of human capital. The analysis shows, for instance, that a major factor driving inequality patterns is the national differences in education systems.

(8) This study uses for the whole population to measure the average and inequality in human capital stock. Because of this, any recent expansion in education is likely to result in greater inequality, because it is only the younger cohorts that increase their education; older cohorts remain at the level that prevailed when they were in the education system. Should this be the case, measures of educational inequality really only pick up a *cohort effect* rather than inequality among people of the same generation. Hence, another step of the analysis would be to calculate educational inequality across different cohorts.

(9) This study deals with the non-spatial econometric literature, and therefore the notion of spatial heterogeneity has concentrated on models of absolute location. The analysis could be extended to *spatial econometrics* as a further line of research. As has been mentioned above, spatial econometrics have concentrated on models of relative location and are tightly linked to the concept of spatial regimes (Abreu et al., 2004). Spatial econometric techniques can provide a natural framework to test for the occurrence of

interregional externalities and to estimate their magnitude (Vaya et al., 2004), but have been known to ignore the time dimension and focus on a single spatial interaction equation (Anselin, 2000). In spatial econometric models, spatial relationships are summarised in a spatial weights matrix. Although the appropriate choice of the spatial weights matrix is one of the most difficult and controversial methodological issues in spatial econometrics, by means of differentiating the operationalisation of the matrix, we are able to distinguish differing hypotheses regarding the interregional interaction through externalities (Vaya et al., 2004). More specifically, the spatial econometric models concern the estimation of spatial lag models and spatial error models, which are usually supported by means of the ML method (Anselin and Bera, 1998; Smirnov and Anselin, 2001) and the GMM (Conley 1999; Kelejian and Prucha, 1999). The spatial heterogeneity could be illustrated by the estimation of the heteroskedastic error model. Three different model specifications are considered for further research. First, the generic heteroskedasticity when urbanisation and latitude are heteroskedastic variables which are squared in the specification of the heteroskedastic error variance. Second, the groupwise heteroskedasticity when the dummies are heteroskedastic variables. This model, for example, tests whether regional economies within a group (northern regions) interact more with one another than with members of the other group (southern regions). Third, the random coefficients when the heteroskedastic variables are constructed as the squares of the explanatory variables in the model. For each model, two estimations are included: the three-step feasible generalised least squares and the ML estimator. Another method in spatial econometrics incorporates spatial effects in the form of spatial filters: spatial autoregressive and spatial moving average filters. Both filters may be used to eliminate spatial dependence in a variable. This method centres on spatial filtering of the existing variables in such a way that one can make use of the OLS estimation (Getis, 1995; Griffith, 2002; Getis and Aldstadt, 2004; Griffith, 2004; Tiefelsdorf and Griffith, 2006). Existing methods developed for dynamic, but non-spatial, and for spatial, but non-dynamic, panel data models produce biased estimates when these models are put together. No straightforward estimation procedure is available (Elhorst, 2001, 2003; Badinger et al., 2004; Elhorst, 2005). Nevertheless, to overcome this deficit, Badinger et al. (2004) propose to employ a two-step procedure; first, a filtering technique as proposed in Getis and Griffith (2002) is applied to remove the spatial correlation from the data; and second, a GMM estimator is applied to make inference on dynamic panel data.

(10) The analysis shows that *space and time* are intrinsically mixed in the process of inequalities and regional economic growth. According to Elhorst (2005), the models for dynamic panels in time and space presented by Anselin (2000) deal with serial dependence between the observations on each region over time (time-series econometrics literature); spatial dependence between the observations on regions at each point in time (spatial cross-section econometrics literature); and unobservable spatial and time period specific effects (panel data econometrics literature). The study of space and time interaction is a hard task (Fujita and Thisse, 1996). Nevertheless, it is a challenge for future empirical research.

Overall, this study provided coherent evidence that income and educational inequalities matter for growth. The analysis undertaken here and the contributions made will constitute a solid basis for regional policy implications and further investigation into the issues addressed.

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