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MEASUREMENT OF REGIONAL ECONOMIC DISPARITIES

Authors:

José Villaverde
Adolfo Maza

The authors

José Villaverde

José Villaverde is professor at the University of Cantabria (Spain).

Department of Economics, University of Cantabria (Spain). Av. Los Castros, s/n. 39005 Santander. E-mail: villavej@unican.es

Adolfo Maza

Adolfo Maza is professor at the University of Cantabria (Spain).

Department of Economics, University of Cantabria (Spain). Av. Los Castros, s/n. 39005 Santander. E-mail: mazaaj@unican.es

Draft Chapter for the forthcoming GARNET Handbook on Monitoring and Analysing Regional Integration Processes

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United Nations University - Comparative Regional Integration Studies
Potterierei 72, 8000 Brugge, BE-Belgium
Tel.: +32 50 47 11 00 / Fax.: +32 50 47 13 09
www.cris.unu.edu

Abstract

Regional disparities have become a hotly debated topic in the last two to three decades. The reason for this increasing interest in regional disparities is twofold: from an applied perspective it should be an issue of political priority in most supra-national integration schemes and it is undoubtedly so in the European Union (EU), as the persistence of important regional disparities is considered to be detrimental for the success of supra-national integration projects; from an academic perspective, the studies on regional disparities and, in particular, of regional convergence are an indirect way of testing the validity of different and competing theories of economic growth and international trade.

There is considerable debate over which technique is the most suitable to measure regional disparities. The main problem in this debate is that the term *disparity* is a multifaceted concept encompassing dimensions such as convergence, inequality and polarisation. Thus, the way of measuring regional disparities is closely linked to the dimension at stake, that is to say, to the research needs. The point is that there are so many disparity indicators that, even when analysing a specific dimension, it is not an easy task to choose among them. This being the case, the best practice usually involves the use of different indicators to measure the same dimension; if all indicators point to the same direction we can be fairly sure that the results are robust.

This is indeed the approach used in this paper. Its main objective is to offer a review of the different ways of looking at regional disparities and, above all, of how to measure them. In doing so, the paper also pays attention to the data requirements and sources needed to compute different types of disparity indicators, and to their main characteristics.

Introduction

In 2007 the European Union (EU) has celebrated its 50th anniversary. Since the signature of the Treaty of Rome in 1957, the EU has undergone a remarkable process of expansion and, so far, a successful integration that has proved very profitable to its country members, not only from an economic point of view but also, and maybe more significantly, from a social and political perspective.

Drawing from this success, many other regions in the world have tried to set up supra-national integration schemes adapted to their specific situation. In the more market driven integration process in Asia, the Association of Southeast Asian Nations (ASEAN) and the South Asia Association for Regional Cooperation (SAARC), and their corresponding free trade areas, are among the most successful processes. In America, both the North American Free Trade Agreement (NAFTA) and the Latin American groupings, Mercosur and Central American Common Market (CACM), stand out as the more relevant ones. There are also interesting but, at least until now, less fruitful attempts of regional integration in Africa, such as the Economic Community of West African States (ECOWAS), the Common Market for Eastern and Southern Africa (COMESA), the Economic Community of Central African States (ECCAS) and the Arab Maghreb Union (AMU). Finally, in Oceania is worth mentioning the Australia New Zealand Closer Economic Relations Trade Agreement (ANZCERTA).

In order for these supra-national integration schemes to have the possibility of being successful, one of the many necessary conditions to be fulfilled by the participating countries and their comprising regions is that the economic disparities among them should not be very high. However, it is convenient to note that the debate about the relationship between international integration and territorial disparities has not arrived to definitive results. According to the traditional Heckscher-Ohlin-Samuelson model, international trade economists come to the conclusion that international economic integration brings about territorial convergence, either as a result of factor mobility or as a consequence of trade relations. A completely different picture is offered by the "new economic geography" pioneered by Krugman (1991a,b); by considering the forces of regional agglomeration spurred on by economic integration, it is highly likely that it will result in an increase of territorial disparities.

Consequently, it is natural that the study of regional disparities has become a heated topic in the last two to three decades. The reason for this increasing interest in regional disparities is twofold: as previously suggested, from an applied perspective it should be an issue of political priority in most supra-national integration schemes and is undoubtedly in the European Union (EU), as the persistence of important regional disparities is considered to be detrimental for the success of supra-national integration projects; from an academic perspective, the studies on regional disparities and, in particular, of regional convergence are an indirect way of testing the validity of different and competing theories of economic growth and international trade.

There is considerable debate over which technique is the most suitable to measure regional disparities. The main problem in this debate is that the term *disparity* is a multifaceted concept encompassing dimensions such as convergence, inequality and polarisation. Thus, the way of measuring regional disparities is closely linked to the dimension at stake, that is to say, to the research needs. The point is that there are so many disparity indicators that, even when analysing a specific dimension, it is not an easy task to choose among them. This being the case, the best practice usually involves the use of different indicators to measure the same dimension; if all indicators point to the same direction we can be fairly sure that the results are robust.

This is indeed the approach used in this paper. As an applied paper, its main objective is to offer a rapid review of the different ways of looking at regional disparities and, above all, of how to measure them. In doing so, the paper also pays attention to the data requirements and sources needed to compute different types of disparity indicators, and to their main characteristics.

The remainder of the paper is organised as follows. Section 2 refers to scope, data and sources. Section 3 reviews some convergence concepts, while Section 4 presents the main inequality and polarisation indicators. Due to the conceptual limitations of these three approaches (convergence, inequality and polarisation) for the study of regional disparity, Section 5 changes the focus and so is devoted to the analysis of the entire distribution, its variations over time and the intra-distributional mobility. Section 6 pays attention to the well-known but often neglected fact of spatial dependence. All the issues considered in Sections 3 to 6 are illustrated with reference to the Spanish regions. Finally, Section 7 presents the concluding remarks.

Regional disparities: Scope, data and sources

General remarks

When dealing with the analysis of regional disparities (either to a national or supra-national level), the first question which has to be asked is as simple as it is important: regional disparities of what? Economists tend to be mainly concerned with income disparities, but the study of disparities in other areas (unemployment, human capital, infrastructures …) is also of great relevance in order to know more about the various paths of the economic growth process in different regions.

Even when the interest is centred on income disparities, the decision about the key variable to be analysed is crucial. Economists commonly consider production (income) per capita and/or labour productivity. Production per capita (the ratio between production and population) refers to the level of income of the entire population whereas labour productivity (the ratio between production and the units of labour employed) measures the efficiency degree of workforce. Although both variables refer to somewhat different things, they not only share the same numerator but the denominators (population and employment) are highly correlated between each other. It is therefore evident that most disparity measures tend to offer relatively similar results for per capita income and productivity; nevertheless, there are always some differences obviously related to the different ratios of employment to population.

Another important aspect is to decide which variable best represents production. Although in many cases Gross Domestic Product (GDP) is considered to be the most suitable option, it all depends on what the specific purpose of the analysis is. Thus, sometimes it may be more adequate to use Gross Value Added (GVA) than GDP, as the former does not include government transfers and indirect taxation, which are included in the latter.

Despite what has been said, it has to be admitted that, more often than not, the choice of the representative variable is determined by the availability of long time-series data. If no long time-series data is available for the most representative variable, it would be preferred to use an alternative closely-matching variable for which adequate data can be found.

Regional disparities at a supra-national level: data, sources and studies

Generally speaking, data on GDP, population and employment are easily available. Institutions like the EU, the Organisation for Economic Cooperation and Development (OECD), the International Monetary Fund (IMF), the World Bank, the University of Pennsylvania (Penn World Tables) and some others related to specific supra-national regional integration agreements (ASEAN, SAARC, Mercosur, NAFTA, etc.), plus many national statistics institutes, offer this kind of information, and for relatively long sample periods, at supra-national, national and/or sub-national levels. With reference to the EU, the most advanced, peaceful integration project in the world, different data banks are available, among which some of the most interesting are AMECO (European Commission), REGIO (EUROSTAT), Cambridge Econometrics and the Total Economy Database (Groningen Growth and Development Centre).

A wide variety of papers has been written on the issue of regional disparities, mainly with reference to the EU. This naturally means that it is nearly impossible to acknowledge all the researchers that have been dealing with this issue. As a short reference to some of the most interesting papers, it is worth mentioning the old but excellent survey edited by Armstrong and Vickerman (1995). More recently, papers like those of Meliciani (2006) or Badinger et al. (2004) and the books edited by Cuadrado-Roura and Parellada (2002) and Fingleton (2003) are very good references. Two main conclusions have been drawn: on one hand, disparities have clearly diminished until the late eighties/early nineties but stalled afterwards; on the other hand, these disparities are lower (and have decreased at a higher rate) when observed with productivity than with per capita income.

Although most of the papers on regional convergence in Europe refer to the *old* EU (EU12 or EU15), some of them also pay attention to the *new* members (Central and Eastern European Countries). By and large these papers conclude that there is convergence between them; however there are sharp differences about whether these countries have converged, or not, with the rest of the EU (Amplatz, 2003; and Matkowski and Próchniak, 2007).

As for the Asian region, the surveys by Togo (2001) and Hill (2002), and the more recent papers by Michelis and Neaime (2004), Lim and McAleer (2004), Sato and Zhang (2006), and Li and Xu (2007) are among the most relevant; the general conclusion of these papers is that although economic integration -through increased trade flows- has been instrumental in reducing income disparities between the Asian countries, there is ample scope for additional reductions.

From the point of view of Latin America, most papers deal either with the whole region or with some specific region, mainly Mercosur and the CACM; the papers by Holmes (2005), Camarero et al. (2006) and Galvâo and Gomes (2007) are, respectively, good examples of the first and second case; for instance, the paper by Camarero et al. (2006) shows the existence of a productivity convergence process which is mainly the result of higher economic integration (as in Asia through increased trade flows) between the Mercosur countries; equally, Holmes (2005) has found evidence of an important convergence process among the CACM country members.

With reference to Africa, there are few studies analysing the processes of economic integration and income convergence; although, generally speaking, the results obtained are mixed, most of them conclude that there is no tendency (or, at least, a clear-cut tendency) to the reduction of disparities and that this is closely linked to the weak growth performance and the low level of regional trade integration among the African countries (Hammouda et al., 2007).

Regional disparities in Spain: data and sources

As for the Spanish case, which is considered for illustrative purposes in this paper, our key variable is per capita income, measured by the ratio GDP/population over the 1985-2005 period. Additionally, the paper also considers variables such as labour productivity and the employment and dependency rates. The data set used was compiled from the Spanish Savings Bank Foundation (FUNCAS).

An important decision in order to carry out this type of analysis pertains to the level of territorial disaggregation to be used. As is shown in Figure 1, Spain is divided into 50 provinces (NUTS 3) which make up 17 autonomous regions (NUTS 2)[1]. Considering that aggregation problems may arise when dealing with regions due to the fact that they are of widely differing sizes and encompass different numbers of provinces (Table 1), we have opted to perform the analysis at provincial level.

Regional convergence

Regional convergence: the basics

As explained in Villaverde (2006) the literature has coined different concepts of convergence. In this paper, and for the sake of simplicity, we refer solely to the three of them which are the most common: absolute β convergence, conditional β convergence, and σ convergence. Intuitively, absolute β convergence implies a tendency for poor regions to catch up with richer regions; as defined in the empirical literature (see, for instance, Barro and Sala-i-Martin, 1992) absolute β convergence deals with the cross-section regression of the income growth on the initial per capita income. The traditional absolute β convergence equation is given by:

$$\left(\frac{1}{T}\right)\log\left(\frac{y_{iT}}{y_{i0}}\right) = c + \beta\log\left(y_{i0}\right) + \mu_i \qquad (1)$$

where c is the constant term, $\beta = -\left(1 - e^{-bT}/T\right)$ is a parameter indicating the relationship between growth and initial income, being b the speed of convergence as defined in endnote 6, y_i refers to per capita income of observation i, T stands for the sample period and μ is the error term. When the regression coefficient on the initial per capita income (β) bears a negative sign (meaning that poor economies grow faster than rich economies), it is said that there exists absolute β convergence.

The difference between absolute (unconditional) and conditional β convergence is related to the parameters determining income in the steady-state: if these are identical across economies there is absolute β convergence, whereas if they are different there is conditional β convergence. The idea is

[1] The Nomenclature of Territorial Units for Statistics (NUTS) was established by Eurostat more than 25 years ago in order to provide a single uniform breakdown of territorial units for the production of regional statistics for the European Union. The NUTS classification is hierarchical in that it subdivides each Member State into three levels: NUTS levels 1, 2 and 3. The second and third levels are subdivisions of the first and second levels respectively.

that absolute convergence relies on the assumption that the only difference across economies is their initial level of per capita income whereas conditional convergence considers that the above mentioned difference is also related to differences in other factors such as technology, infrastructures, the propensity to save, the industrial mix, etc. In the first case, the steady-state will be the same for all economies. In the second each economy tends towards its own steady-state, so relative income tends to stabilise over time; this means that, when dealing with conditional convergence, the emphasis should be on the structural determinants of income. The classical equation for conditional β convergence is given by the expression:

$$\left(\frac{1}{T}\right)\log\left(\frac{y_{iT}}{y_{i0}}\right)=c+\beta\log\left(y_{i0}\right)+\gamma X_i^{'}+\mu_i \qquad (2)$$

where $X_i^{'}$ is a vector of conditioning variables.

Finally, σ convergence pertains to the reduction of the cross-sectional dispersion in per capita income over time; this simply means that, in truth, σ convergence is a way of looking at income inequality[2]. Although the evolution of any indicator of inequality can be considered as a measure of σ convergence (or divergence), the specialised literature usually employs indicators such as the variance (standard deviation) or the coefficient of variation. In this paper we have opted for using the coefficient of variation as the variance value depends on the measurement unit employed. The coefficient of variation (σ) is given by the expression:

$$\sigma = s/\overline{y} \qquad (3)$$

where *s* stands for the standard deviation and $\overline{y}$ is the mean of the distribution.

Regional convergence in Spain

In this subsection we apply these three concepts of convergence to Spain. In particular, the presence of absolute β convergence among the Spanish provinces is examined in Figure 2; this suggests that this process has occurred. To confirm this we have estimated Equation (1) by ordinary least squares. It is crystal clear (Table 2) that there is a process of absolute β convergence, as indicated by the fact that the coefficient of (the log of) per capita income in the base year (1985) is negative and highly

[2] As the concepts of β and σ convergence are jointly treated in the specialised literature, we have considered σ convergence in this section instead of that of inequality.

significant. The speed of convergence is 1.48 per year, this meaning that the time needed to cover half the gap to the steady-state is slightly less than 40 years[3].

The concept of absolute β convergence is thought to be too restrictive as it requires that all provinces approach the same rate of equilibrium growth. Thus, in order to consider the possibility of different rates of equilibrium growth, a conditional β convergence equation (capturing any possible differences in the steady-state across provinces) should be estimated. Although to do this it would be useful to consider a wide array of variables related to the structural determinants of income, for illustrative purposes we have considered only two additional explanatory variables: the first one (*H*) captures the effect that human capital[4] in the initial year has on the rate of growth of per capita income; the second variable (*Agr*) measures the share of agricultural GDP in total GDP in the base year. Once again, the estimation of Equation 2 including these two variables separately shows (see Table 2)[5] that, as expected, all the coefficients are statistically significant and the fit of the regression equations improves. In particular, it can be seen that β increases, this meaning that the speed of convergence is much higher in both cases of conditional convergence than in that of absolute convergence; this in turn implies that the half-life is strongly reduced. Additionally, it is shown that the coefficient of human capital is positive: provinces with better initial human capital endowments grew at faster rates. The coefficient for the agriculture variable has, on the contrary, a negative sign, indicating that the provinces with a greater share of agriculture in total GDP grew more slowly.

As for the σ convergence, the results obtained by using Equation (3) are displayed in Figure 3. Two main conclusions can be obtained. First, a process of σ convergence has undoubtedly developed over the sample period. And second, and with the exceptions of 1995 and 2000, the rate of σ convergence has been quite stable over the sample period. In our opinion, this process (which to a lesser extent had

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[3] The speed of convergence (b) is the rate at which income approaches its steady state relative to its distance from its steady state. Given that $\beta = -\left(1 - e^{-bT}/T\right)$, if we solve this expression for b we obtain that b=$-\log\left[1 - \beta T\right]/T$.

The half-life is the number of years required to eliminate one half of the initial deviation of y_i from its steady state value (y^*). The transitional dynamics of equation (1) is given by $\log y_{\mathrm{it}} - \log y^* = e^{-bT}(\log y_{io} - \log y^*)$. As we want to cover half the gap to the steady state, we substitute the first part of this equation $(\log y_{\mathrm{it}} - \log y^*)$ by $0.5(\log y_{io} - \log y^*)$. Then we have that $0.5(\log y_{io} - \log y^*) = e^{-bT}(\log y_{io} - \log y^*)$, and solving for T we obtain that the half life is equal to $-\log(0.5)/b$.

[4] For the human capital indicator we have used the expression: $H = \sum_{i=1}^{5} \phi_i A_i$, where ϕ_i stands for the weight attached to human capital of level *i* and *A* (number of study years) takes the values 0, 4, 8, 12 and 16 for i= 1, 2, 3, 4 and 5, where 1=Illiterate, 2=No formal education or primary education, 3=Compulsory secondary education, 4=Pre-university education, and 5=Higher education.

[5] Although the two variables could have been considered jointly, we believe that, for the sake of easy interpretation of the results, it is better to consider them separately.

already taken place previously to our sample period) has been enhanced by the three main steps of Spain's integration into the EU: its accession in 1986, and the launching and implementation of both the Single Market programme (first half of the 1990s) and the Monetary Union (second half of the 1990s and first part of the 2000s).

In order to know which provinces have contributed most to this σ convergence process we have broken our sample into three groups according to their relative per capita income: less than 90%, between 90 and 110% and more than 110%[6]. As can be seen in Figure 4, a striking result emerges: of these three groups, the only one that has clearly experienced a process of σ convergence has been that of the richest provinces, and this only up to the mid-nineties, for since then a process of σ divergence has taken place. This same σ divergence process has happened over the whole period of the analysis within the middle-income group, while the group including the poorest provinces has roughly maintained its degree of dispersion. These results point to the fact that the σ convergence process has happened more inter-groups than intra-groups; in fact, when computed, the intra-groups σ convergence as the weighted average of the three groups σ convergence values and the inter-groups σ convergence as the difference between total and intra-groups σ convergence, it can be seen (Figure 5) that total σ convergence is simply the result of inter-groups convergence as intra-groups dispersion has tended to be quite stable over time.

Regional inequality

Regional inequality: the basics

Before analysing the issue of regional inequality it is necessary to clarify what is understood by the term *inequality*. To begin with, it should be admitted that inequality, as a not self-defining concept, is an awkward word. Then, it is no wonder that inequality is generally defined in a negative way; as indicated by Cowell, (1995, p.1) "*inequality obviously suggests a departure from some idea of equality*". Although the term equality may have different meanings, in this paper it is considered in its simplest sense that two or more quantities are the same.

While initially devised to address inequality issues between individuals, most of the indicators can easily be adapted to dealing with per capita income inequality among regions. As there is no accepted best measure of income inequality, in this section we review the most commonly used inequality

[6] The number of groups is, to a given extent, arbitrary. When it comes to the choice of them, the researcher should weight the clarity of the results and the number of observations in each group.

indicators: after having considered the coefficient of variation in the previous section, here we pay attention to the Gini index, two versions of the Theil index and the Atkinson index.

The Gini index (G) is a descriptive inequality indicator closely linked to the Lorenz curve, this measuring the proportion of total income in the hands of a given percentage of population. This index is calculated as the ratio of the area between the Lorenz curve and the 45º line[7] to the whole area below the 45º line (Villaverde, 2006). In formal terms, its expression can be written as:

$$G = \frac{1}{2\overline{y}} \sum_{i=1}^{n} \sum_{j=1}^{n} p_i p_j \left| y_i - y_j \right| \tag{4}$$

where n stands for the number of observations, p_i and p_j refer to the population shares of observations i and j and $\overline{y}$ is the mean per capita income[8]. The value of the index ranges from 0 (complete equality) to 1 (complete inequality).

The Theil index follows a descriptive approach to inequality which, as for the Gini index, does not involve welfare judgements. The Theil index is an inequality indicator based on the concept of entropy, a concept that –when applied to income distributions- refers to deviations from perfect equality[9]. In general terms, a generalised entropy inequality index can be expressed as:

$$E(\alpha) = \frac{1}{n\left(\alpha^2 - \alpha\right)} \sum_{i=1}^{n} \left[\left(\frac{y_i}{\overline{y}} \right)^{\alpha} - 1 \right] \tag{5}$$

where α captures the sensitivity of E to a particular part of the income distribution[10]. Usually α takes the values 0 and/or 1. For $\alpha=0$ the Equation (5) becomes:

$$T(0) = -\frac{1}{n} \sum_{i=1}^{n} \log\left(\frac{y_i}{\overline{y}} \right) \tag{6}$$

whereas for $\alpha=1$ the index is given by the expression:

$$T(1) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i}{\overline{y}} \right) \log\left(\frac{y_i}{\overline{y}} \right) \tag{7}$$

[7] If all incomes were equally distributed the Lorenz curve would follow the 45º line. This is also called the equidistribution line.

[8] For the sake of simplicity we have omitted from this and the following expressions the subscript t (for time).

[9] For a thorough reference to the relationship between Theil measures of inequality and the concept of entropy, see Cowell (1995).

[10] When positive, the larger (smaller) the value of □, the more sensitive will the index to what happens in the upper (bottom) tail of the income distribution be.

Contrary to the two previous indices, the Theil index does not have a constant defined upper limit; it ranges from 0 to log(n), with higher values showing a more unequal income distribution.

One of the more interesting advantages of the Theil index is that it is additively decomposable and admits different types of decomposition. In particular, in this paper we consider two different (and somewhat complementary) ways of decomposition. On one hand, and taking into account that the GDP per capita can be decomposed according to the expression:

$$\text{GDP per capita} = y = \frac{Y}{E}\frac{E}{A}\frac{A}{P} \tag{8}$$

where Y, P, E and A stand for income, population, employment and active population, the general Theil index can also be decomposed in the sum of three partial Theil indices: one for productivity (*Y/E*), one for the employment rate (*E/A*), and one for the dependency rate (*A/P*). This means that, for instance, the T(1) index can be re-expressed as:

$$T(1) = \sum_{k=1}^{m} \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i^k}{\bar{y}} \right) \log\left(\frac{y_i}{\bar{y}} \right) \tag{9}$$

where k (1,2,3) stands for the three income sources: 1 for productivity, 2 for the employment rate, and 3 for the demographic component (dependency rate).

On the other hand, if we consider that the observations can be grouped into mutually exclusive and completely exhaustive groups, then the Theil index can be decomposed in a between-groups component (Theil-between) and a within-group component (Theil-within); the first captures the inequality due to the variability of income across groups while the second captures the variability of income within each group. In formal terms, the T(1) index can be re-expressed as:

$$T(1) = \sum_{k=1}^{m} \left(\frac{n_k}{n} \frac{\bar{y}_k}{\bar{y}} \right) T_k + \sum_{k=1}^{m} \frac{n_k}{n} \left(\frac{\bar{y}_k}{\bar{y}} \right) \log\left(\frac{\bar{y}_k}{\bar{y}} \right) \tag{10}$$

where the first term on the right hand-side of the equation is the weighted average of the Theil inequality indices of each group (T_k) and the second term is the T(1) index calculated using subgroups means $\bar{y}_k$ instead of actual incomes. The first term is the Theil-within while the second is the Theil-between.

Finally, the Atkinson index is a welfare-based measure of inequality because explicitly incorporates normative judgments about social welfare[11]; in particular, this index is more "bottom-sensitive" than other inequality indices. The Atkinson index can be expressed as:

$$A_\varepsilon = 1 - \left[\sum_{i=1}^{n} p_i \left(\frac{y_i}{\bar{y}} \right)^{1-\varepsilon} \right]^{1/(1-\varepsilon)} \tag{11}$$

where p_i refers to the population share of observation *i* and the parameter ε stands for the degree of inequality aversion[12]; in particular, when ε is positive there is a social preference for equality (or aversion to inequality) and, as ε rises, more (less) weight is attached to income transfers at the lower (top) end of the distribution. The value of the index lies between 0 and 1; the lower the value of the index the more equal the income distribution is.

To conclude, we consider the concept of polarisation, which is closely related to that of inequality, but somewhat different to it (Villaverde, 2006). Generally speaking, it can be said that the polarisation of the regional income distribution reflects the degree to which regions cluster around a series of income poles (intervals of income). Following Esteban and Ray (1994), the simplest polarisation index (*P*) can be expressed as:

$$P = \frac{1}{\bar{y}} \sum_{i=1}^{k} p_i^{1+a} p_j \left| y_i - y_j \right| \tag{12}$$

where a is a parameter denoting the degree of sensibility of the index to polarisation, which by construction takes values between 1 and 1.6[13], *k* is the number of groups (poles) previously defined, p_i and p_j are the relative population of group *i* and *j*, and y_i and y_j are the average per capita income of both groups. Although, apparently, the algebraic expression of *P* is rather similar to that of *G*, the fact that p_i is raised to (1+*a*) means that the measure of *P* follows a different pattern than that

[11] The main advantage of welfare-based measures is that they provide for a complete and cardinal ordering. To do that, it is needed to specify the exact form of the social welfare function. This implies, and this is also their main drawback, that the results critically depend on this functional specification. As for the descriptive measures of inequality, which do not need an exact specification of the social welfare function, their main disadvantage is that they offer a partial and ordinal ranking; on the other side, their main advantage is the robustness of the results. A complete (partial) ranking implies that income distributions can (cannot) be ranked; a cardinal ranking indicates by how much a distribution is preferred to other, whereas an ordinal ranking says that one is preferred to the other but not by how much.

[12] Put it another way, □ reflects the strength of society's preference for equality. This parameter can take values from zero to infinity.

[13] The value of *a*, which does not depends on the number of income poles, falls in the interval [1, 1.6] in order to be consistent with a set of axioms. For a complete derivation of it, see Esteban and Ray (1994).

of G; in fact, the conceptual difference between inequality (as measured for G) and polarisation is greater the higher the value of a[14].

Regional inequality in Spain

Although, in the context of convergence, we have previously addressed the issue of regional inequality in Spain, in this Sub-section we are going to deal with it more in depth, by way of applying the above mentioned inequality indices. The results are shown in Table 3 and Figures 6 to 8.

Regarding to the Gini index (Equation 4), the main conclusion is that provincial disparities in Spain have declined over time. On average, inequality between Spanish provinces has declined by about 8%.

The results obtained for the Theil indices (Equations 6 and 7) are roughly the same as those of the Gini index, that is, provincial income inequality declines over time, but with some ups and downs. However, there exists an important difference between these two indices: the reduction in the degree of provincial inequality is much more pronounced for the Theil indices than for the Gini index.

With reference to the decomposition of total inequality according to the Theil index (Equation 9), it can be seen that, according to the first method, the employment rate has, consistently, the lowest influence on total inequality (Figure 6). On the contrary, the main sources of provincial income inequality are provincial differences in productivity and in the dependency rate: in particular, from 1985 to 2000, the weight attached to productivity differences steadily dropped while that attached to the dependency rate increased; however, from 2000 to 2005 the role played by these two components was roughly of the same magnitude.

As regards the second method of decomposing the Theil index (Equation 10), we have grouped the provinces into regions (see Table 1). Two main conclusions emerge (Figure 7): first, that, even though seven regions are made up of only one province, which may lead to an underestimate of the within-inequality component, most of the total inequality rests on it (that is, inequality between provinces of the same region); second, that the relevance of within-inequality has been fairly stable up until 2000 but, from this year on, it has declined at a very quick rate.

Finally, two main conclusions, very similar to those obtained for the Gini and Theil indices, can be drawn from the values of the Atkinson index (Equation 11): first, the inequality between provinces in Spain has declined, on average, by about 17%, but by more the higher the degree of inequality aversion (Table 3); second, the lower the degree of inequality aversion, the lower the level of and the change in absolute provincial inequality. The normalisation of the values of the three types of indices

[14] As shown in Gradin (2000, p. 459) "the smaller the sensitivity to polarisation, the closer the notion of polarisation to inequality. Indeed, if a =0 the index is a scalar transformation of Gini".

(making their values in 1985=100) shows that all of them have followed a similar pattern (Figure 8), this making the results regards the reduction of provincial per capita inequality in Spain more robust[15].

Having analysed the evolution of provincial inequality in Spain, let us briefly look at the polarisation of the provincial income distribution (Equation 12). In particular, we consider the evolution of polarisation in the provincial per capita income in Spain, for a=1 and 1.5, and under the assumption that the original distribution has been partitioned into two and three groups (bipolarisation and tripolarisation[16]). The results are displayed in Table 4 and, for normalised values, in Figure 9[17]. Although there are some differences depending on the value of a, three main conclusions can be obtained: 1.- The decade between 1985 and 1995 witnessed a relatively stable value of the polarisation index, which steadily declined from 1995 to 1999; 2.- In 2000 the index experienced a sudden and huge increase[18]; 3.- From 2000 to 2005 the index once again declined at an even more rapid pace than before. To finish, a quick glance at Figures 8 and 9 shows that, although representing different things, inequality and polarisation indices have about followed the same time-pattern.

Regional income distribution

Regional income distribution: the basics

So far our attention has been focused on the analysis of convergence and inequality. However interesting this type of analysis is, it has some drawbacks. As indicated by Quah (1996), a major limitation of this approach is that it does not inform either about changes in the shape of the distribution or about the fact that some regions may shift their relative positions during the period of study. To tackle these problems, in this section we complete the previous analysis by considering, first, the changes that have occurred in the regional income distribution over time and, second, the intra-distributional dynamics.

In order to highlight the external shape of the distribution, we propose to estimate univariate density functions. A density function is a smooth curve which represents the probability distribution of a continuous random variable. The density function is estimated non-parametrically by the kernel method. In formal terms, the kernel density estimate of a series X at a point x is given by the expression:

[15] Otherwise, the researcher should make a choice as to which index is more suitable for the purpose of the research.
[16] The number of poles (groups) is, once again, arbitrary. We have considered that the dividing line between the two groups in the first case is the average per capita income, while the groups in the case of tripolarisation are composed by provinces according to their relative per capita income: less than 90%, between 90 and 110%, and more than 110%.
[17] For reasons of simplicity, only the case of a=1.5 is shown in this figure. As can be seen in Table 4, the graphical representation would be very similar for a=1.
[18] Although the data base is theoretically homogeneous, a possible explanation for this change could be of a statistical nature.

$$f\left(x\right)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x-X_i}{h}\right) \qquad (13)$$

where, as always, n is the number of observations, whereas K is the kernel function, h the smoothing parameter, X_i the values of the independent variable and x the value of the independent variable for which one seeks an estimate. Intuitively, this method consists of choosing a narrow interval (the so-called smoothing parameter or bandwidth) around the point x and estimating $f(x)$ by the number of observations X_i belonging to the interval. The kernel function is a weighting function giving the weights of the nearby data points in making this estimate[19].

In addition to knowing the changes in the external shape of the given distribution, it is of interest what happens within it. In fact, and according to Quah (1997), movements within the distribution are even more important than changes in its external shape. The easiest way of analysing the importance of intra-distribution mobility is to calculate the well-known transition matrices. Thus, if F_0 and F_t refer to the initial and final distributions, the link between them can be defined as $F_t = M^t *F_0$, where M^t represents the transition probability matrix. Operator M^t is approximated by dividing the income distribution into intervals or "income states"; unfortunately, due to the lack of sound theoretical methods to obtain an appropriate partition of the distribution, the selection of "per capita income states" is somewhat arbitrary and the results obtained by using this approach critically depend on the number and length of the intervals considered for the original distribution[20].

Finally, and under the assumption that past tendencies will go on in the future, it is also interesting to know the shape of the income distribution in the long-run equilibrium; this is what is called "ergodic distribution". This distribution is computed by raising the transition matrix to the power of k (k being a large enough number) so that the result is a new matrix in which all rows have the same values.

[19] We have used a Gaussian kernel with optimal bandwidth, following Silverman's rule (Silverman, 1986). This Gaussian Kernel is given by the expression:

$$\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}u^2\right)$$

where u is the argument of the kernel function. As for the bandwidth, the expression used by Silverman is $h = 0.9n^{-1/5}\min\left[s, R/1.34\right]$, where s is the standard deviation and R the interquartile range of the series.

[20] Some authors (Quah, 1997; Stokey and Lucas, 1989, among others) prefer to analyse the intra-distribution dynamics by means of an approach based on the estimation of stochastic kernels. These are the equivalent of a transition matrix where the number of intervals tends to infinity. This approach has been used to examine the Spanish case in, for example, Maza and Villaverde (2004) and Villaverde and Maza (2008).

Regional income distribution in Spain

In order to illustrate the appeal of the previous concepts, once again we have applied them to the Spanish economy. Thus, we begin with the analysis of the external shape of provincial income distribution in Spain and its changes during the 1985-2005 period (Equation 13). In so doing, the results displayed in Figure 10 allow us to obtain the following conclusions: 1.- The aforementioned convergence process between the Spanish provinces is confirmed. As can be seen, the distribution is more concentrated around the mean in 2005 than in 1985 and also shows a reduction in the ratio of extreme values; 2.- The distribution presents only a main mode in 2005 (for per capita income levels around 80% of the Spanish average) while it clearly presented two modes in 1985.

After having compared the external shape of the provincial per capita income distribution in the initial and final years of our sample, we pay attention to its intra-distributional dynamics, for which we have considered the following five income states: $60 \geq 1 > 75$; $75 \geq 2 > 90$; $90 \geq 3 > 110$; $110 \geq 4 > 125$; $125 \geq 5 > 175$[21].

The results obtained for the whole period are presented in Table 5, where the first row and column represent the different income states for 1985 (first column) and 2005 (first row), while the second column indicates the number of provinces of each income state in 1985 and the second row gives the same information, but for the year 2005. As for the transition matrix, the entries in each cell are the probabilities associated with each transition. Therefore, the main diagonal of the table indicates persistence (provinces belonging to the same state in 1985 and 2005); on the contrary, the cells over (under) the diagonal represent upwards (downwards) mobility, that is, provinces that have transited from one state i to another state j. The main conclusions of this analysis can be summarised as follows: 1.- The mobility within the per capita income distribution is relatively high; 27 Spanish provinces have moved from one state to another in our sample period. 2.- The mobility is specially high in the first state considered ($60 \geq 1 > 75$); in this case, 10 out of 15 provinces have transited to the immediate upper state; 3.- In general terms, most of the mobility occurs towards the next state and is upwards mobility.

In addition to the aforementioned drawbacks, another criticism of the computation of the previous transition matrix is that it only considers data on the initial and final years of the sample period. To solve this problem we have also calculated a step-by-step transition matrix, this indicating that, first, we have computed a transition matrix for every two consecutive years and, second, we have multiplied

[21] We have considered five "states" (groups) instead of three (as in Section 3) in order not to mask the intra-distributional mobility degree. As it is easy to understand, the lower the number of "states", the lower the intra-distributional mobility degree.

them[22]. The results obtained, displayed in Table 6, illustrate that the main differences with the one-step matrix (Table 5) are related to the mobility degree of provinces with the highest income levels.

Besides this, Table 6 shows the initial, final and ergodic distributions. The comparison between the initial and final distribution corroborates that a convergence process has occurred between 1985 and 2005, while the values for the ergodic distribution show that this convergence process will continue in the future, as is clearly indicated by the fact that the number of provinces belonging to the first and fifth states declines.

Regional convergence and spatial dependence

Regional convergence and spatial dependence: the basics

The classical analysis of β convergence that was presented in Sub-section 3.1 does not consider the spatial location of the observations; that is to say, it overlooks the fact that regional data can be spatially autocorrelated as similar regions tend to cluster. *"Implicitly, each region has been viewed as an independent entity and the potential for observational interactions across space has gone largely ignored*" (Rey and Montouri, 1999, p. 145). In fact, another important issue related to economic disparities is the concept of "remoteness", that is, the different situation of central and peripheral areas in order to achieve a per capita income level; as it is obvious, regions with better access to input materials and markets should be, all the other things equal, more competitive and hence more successful than more remote regions, which again leads to think in the formation of groups of similar regions.

From an econometric perspective, spatial dependence between observations leads to inefficient estimators and unreliable statistical inference. For this reason, models using geographical data should be systematically tested for spatial dependence, defined as the coincidence of value similarity and locational similarity (Anselin, 2001).

The simplest test for spatial autocorrelation is Moran's I statistic expressed as:

$$I = \frac{n}{s} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2} \qquad (14)$$

[22] To be precise, the step-by-step transition matrix has been computed employing the Chapman-Kolmogorov equation. In other words, this matrix is the result of multiplying the transition matrices between every two correlative years.

where n is, again, the number of observations, z_i and z_j the log of per capita income of each region, w_{ij} the elements of the row-standardised distance matrix W (that is, a matrix in which each row sums to one), and s the sum of all elements of W.

If the previous exploratory spatial data analysis shows the presence of spatial dependence, it should be carried out a confirmatory spatial analysis in the classical β convergence equations. Formally, there might be substantive spatial dependence and/or nuisance spatial dependence. The first happens when the behaviour of regions directly affects the behaviour of neighbouring regions, while the second reflects the existence of a measurement error problem.

Thus, in order to identify which kind of spatial dependence is present in the β convergence equations, the so-called Lagrange Multiplier tests and their robust versions should be performed; these tests are based on the principle of maximum likelihood (for more details, see Rey and Montouri, 1999). Specifically, the test known as the Lagrange multiplier for spatial errors (or LM-ERR), along with the associated robust LM-EL, test for the absence of residual spatial autocorrelation, which would be caused by not including a structure of spatial dependence in the error term. However, the test known as the Lagrange multiplier for spatial lags (or LM-LAG), and its associated robust LM-LE, test for the absence of substantive spatial autocorrelation, which would be due to the spatial correlation in the endogenous variable. In this respect, if the tests are significant, changes should be made to the classical β convergence equations. There are two possibilities: introduce an autoregressive structure in the error term if there is residual spatial dependence, or include a spatial lag of the endogenous variable if there is substantive spatial autocorrelation[23]. When both types of spatial autocorrelation are present, we decide which is predominant by comparing the value of the tests in the two cases and choosing the one with the highest value. In formal terms, if there is residual spatial dependence, the new error term in classical convergence equations must be given by the expression:

$$\mu_t = \lambda W \mu_t + \upsilon_t \tag{15}$$

where λ is a scalar spatial error coefficient and υ_t is normally distributed with zero mean and a constant variance. On the other hand, if there is substantive spatial dependence, a spatial lag model must be estimated; for instance, with reference to the absolute β convergence equation, its new specification would be as follows:

[23] As well as other possibilities, such as including spatial lags of the explanatory variables.

$$\left(\frac{1}{T}\right)\log\left(\frac{y_{iT}}{y_{i0}}\right)=c+\beta\log\left(y_{i0}\right)+\alpha W\_\left[\left(\frac{1}{T}\right)\log\left(\frac{y_{iT}}{y_{i0}}\right)\right]+\mu_i \qquad (16)$$

where, in addition to the variables considered in the classical convergence equation, we include the term "$W\_\left[\left(\frac{1}{T}\right)\log\left(\frac{y_{iT}}{y_{i0}}\right)\right]$", which measures the spatial lag of the endogenous variable.

Regional convergence and spatial dependence in Spain

To apply Moran's I (Equation 14) to the provincial per capita income in Spain we have employed as the distance matrix the inverse of the standardised distance between provincial capitals[24]. The results obtained indicate (Table 7) that, apart from the first five years, there is strong evidence of spatial dependence, as shown by the fact that the statistics are highly significant for all years.

Therefore, we have tested for the presence of substantive and/or residual spatial dependence in our estimated β convergence equations (see Sub-section 3.2). The results obtained (Table 8) show that, for both the absolute and human capital conditional β convergence equations, LM-EL and LM-LE tests are significant; however, for the agriculture conditional β convergence the tests show there are no signs of spatial dependence. Regarding the first two cases, since LM-EL is more significant than LM-LE, we consider the so-called spatial error model as the best specification; this means than in Equations (1) and (2) a parameter measuring the intensity of spatial dependence between the residuals is included (Equation 15).

The estimation results obtained by maximum likelihood[25] are presented in Table 9. First of all, different goodness-of-fit measures -the logarithm of maximum likelihood (LIK), Akaike's information criterion (AIC) and the Schwartz criterion (SC)- show that the spatial equation achieves a better fit than the traditional one[26]. Second, a positive and significant spatial autocorrelation of the error term is found. Finally, and with regard to the speed of convergence, the most noteworthy finding is that this substantially increases, passing from 1.48 to 1.71% annually for absolute β convergence and from 2.28 to 2.45% for human capital conditional β convergence; as a result, the period required to cover half the gap to the steady state falls from 39.6 to 33.1 years in the first case and from 22.8 to 20.5 in the second.

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[24] That is, we attach a higher weight to the nearest provinces than to the most distant provinces.
[25] As Anselin (1988) indicates, the estimation of a spatial error model by ordinary least squares is inconsistent.
[26] It should be pointed out that the traditional measure of fitness (R^2) is unreliable because of the inclusion of spatial errors. For the sake of comparison, the values of these coefficients in the estimation of the classical absolute β convergence are as follows: LIK=187.12, AIC=-370.24 and SC=-366.42; for the human capital conditional β convergence these values are 195.92, -385.85 and -380.11, respectively.

Concluding remarks

This paper has been devoted to the measurement of regional disparities. Thus, we have presented a box of tools to measure the degree and evolution of per capita income territorial disparities and applied it to the Spanish case, which is used as a sort of laboratory[27].

We have begun by considering that analysis of income disparities can be looked at from the point of view of income convergence/divergence. Regarding this subject we have introduced the concepts and formulae of (absolute and conditional) β convergence and σ convergence, and applied them to the Spanish provinces. The results obtained show that, for the period 1985-2005, a process of both (absolute and conditional) β and σ convergence has occurred in Spain; as regards β convergence, it so happens that the speed of convergence is higher in the conditional case than in the absolute one.

Secondly, we have analysed income disparities from the perspective of inequality. Here we have considered three of the most conventional inequality indicators (Gini, Theil and Atkinson) and, once again, have calculated their values for the Spanish case. The main conclusion is that whichever the indicator employed, provincial income inequality has declined over time. Additionally, and bearing in mind the decomposability properties of the Theil index, we have made use of them in two different ways: first, to show that most of the income inequality between the Spanish provinces lies in productivity and demographic differences; second, that overall inequality is mainly of the within-inequality type (inequality between provinces of the same region).

Polarisation, as a different concept from inequality, is also analysed in the paper. To this end, the use of the simplest expression defined to measure this phenomenon indicates that, as for the Spanish case, the degree of polarisation in provincial per capita income has been very low and quite stable over the sample period.

All the indicators used to measure different dimensions of regional income disparities have some drawbacks, mainly that they pay attention only to some specific values of the income distribution. To face this problem, we have tried to understand what happens to the entire distribution and do that by means of computing the so-called density functions and transition matrices. These two tools have allowed us to, firstly, assert that the shape of the distribution has changed, confirming the convergence process between the Spanish provinces, and, secondly, that the mobility degree in the Spanish provincial income distribution has been relatively high.

[27] The software employed in each section of the paper is shown in the Annex.

Finally, the paper refers to a topic that is traditionally lacking in the studies of territorial disparities. This refers to the issue that each region (province in our study) is conventionally considered as an "island" completely independent of all the other regions. As in most circumstances this is not the case, we have introduced some spatial statistics and econometric techniques to deal with this matter. In particular, we examine for the presence of spatial effects in the per capita income distribution (by looking at Moran's I statistic) and in the previously estimated β convergence equations (by means of using the Lagrange multiplier tests). The application of these techniques to the Spanish situation has shown the presence of spatial dependence and, after this being adequately treated in the β convergence equations, it is shown that the speed of convergence increases.

References

Amplatz, C. (2003) The economic convergence performance of Central and Eastern European countries. *Economics of Planning* 36, 273-295.

Anselin, L. (1988) *Spatial Econometrics: Methods and Models*. Kluwer, Dordrecht.

Anselin, L. (2001) Spatial econometrics. In Baltagi, B. (ed.), *A companion to theoretical econometrics*. Basil Blackwell, Oxford, pp. 310-330.

Armstrong, H.W. and Vickerman, R.W. (Eds.) (1995) *Convergence and Divergence among European Regions*. Pion Ltd.

Badinger, H., Müller, W.G. and Tonld, G. (2004) Regional convergence in the European Union, 1985-1999: A spatial dynamic panel analysis. *Regional Studies* 38 (3), 241-253.

Barro, R. and Sala-i-Martin, X. (1992) Convergence. *Journal of Political Economy* 100 (21), 223-251.

Camarero, M., Flores, R.G. and Tamarit, C.R. (2006) Monetary union and productivity differences in Mercosur countries. *Journal of Policy Modeling* 28 (1), 53-66.

Cowell, F.A. (1995) *Measuring Inequality*. Prentice Hall, London.

Cuadrado-Roura, J.R. and Parellada, M. (Eds.) (2002) *Regional Convergence in the European Union*. Springer, Berlin and New York.

Esteban, J.M. and Ray, D. (1994) On the measurement of polarization. *Econometrica* 62, 819-852.

Fingleton, B. (Ed.) (2003) *European Regional Growth*. Springer, Berlín.

Galvâo, A.F. and Gomes, R. (2007) Convergence or divergence in Latin America? A time series analysis. *Applied Economics* 39 (11), 1353-1360.

Gradin, C. (2000) Polarization by sub-populations in Spain, 1973-91. *Review of Income and Wealth*, 46 (4), 457-474.

Hammouda, H.B., Karingi, S.N., Njugna, A.E. and Jallab, M.S. (2007) Why doesn't regional integration improve income convergence in Africa?. Paper presented to the African Economic Conference, Addis Ababa, Ethiopia.

Hill, H. (2002) Spatial disparities in developing East Asia: A survey. *Asian-Pacific Economic Literature* 16 (1), 10-35.

Holmes, M.J. (2005) New evidence on the long-run output convergence among Latin American countries. *Journal of Applied Economics*, 8 (2), 299-319.

Krugman, P, (1991a) Increasing returns and economic geography. *Journal of Political Economy* 99, 483-499.

Krugman, P. (1991b) *Geography and Trade*. MIT Press, Cambridge, MA.

Li, H. and Xu, Z. (2007) Economic convergence in seven Asian economies. *Review of Development Economics* 11 (3), 531-549.

Lim, L.K. and McAleer, M. (2004) Convergence and catching up in ASEAN: A comparative analysis. *Applied Economics* 36 (2), 137-153.

Matkowski, Z. and Próchniak, M. (2007) Economic convergence between the CEE-8 and the European Union. *Eastern European Economics* 45 (1), 59-76.

Maza, A. and Villaverde, J. (2004) Regional disparities in the EU: Mobility and polarisation. *Applied Economics Letters* 11 (8), 517-522.

Meliciani, V. (2006) Income and employment disparities across European regions: The role of national and spatial factors. *Regional Studies* 40 (1), 75-91.

Michelis, L. and Neaime, S. (2004) Income convergence in the Asia-Pacific region. *Journal of Economic Integration* 19 (3), 470-498.

Quah, D. (1996) Regional convergence clusters in Europe. *European Economic Review* 40 (3-5), 951-958.

Quah, D. (1997) Empirics for growth and distribution: Stratification, polarization, and convergence clubs. *Journal of Economic Growth* 2, 27-59.

Rey, S. and Montouri, B. (1999) US regional income convergence: A spatial econometric approach. *Regional Studies* 33 (2), 143-156.

Sato, K. and Zhang, Z. (2006) Real output co-movements in East Asia: Any evidence for a monetary union? *The World Economy*, 29 (12), 1671-1689.

Silverman, B.W. (1986) *Density Estimation for Statistics and Data Analysis.* Chapman and Hall, London.

Stokey, N. and Lucas, R. (1989) *Recursive methods in economic dynamics.* Harvard University Press, Cambridge, Mass. and London.

Togo, K. (2001) A brief survey on regional convergence in East Asian Economies. Musashi University Working Paper 5.

Villaverde, J. (2006) Indicators of regional economic convergence. In: De Lombaerde P. (ed.), *Assessment and Measurement of Regional Integration*, Routledge, London, pp. 146-161.

Villaverde, J. and Maza, A. (2008) Productivity convergence in the European regions, 1980-2003: A sectoral and spatial approach. *Applied Economics* (forthcoming).

Annex: Software employed in each section

Section 3. Regional convergence in Spain

β convergence: Eviews 5.0.

σ convergence: Microsoft Excel 2002

Section 4. Regional inequality in Spain

Inequality indexes (Atkinson, Gini, Theil): RATS 4.20. The RATS routines used can be downloaded from www.ivie.es

Polarisation index: Microsoft Excel 2002

Section 5. Regional income distribution in Spain

Density functions: Eviews 5.0.

Transition matrixes: Microsoft Excel 2002

Section 6. Regional convergence in Spain revisited: The case for spatial dependence

Moran's I statistic: SpaceStat 1.91 along with ArcView GIS 3.2

β convergence spatial contrasts: SpaceStat 1.91 along with ArcView GIS 3.2

β convergence spatial estimation: SpaceStat 1.91 along with ArcView GIS 3.2

Table 1 Summary statistics for the Spanish regions and provinces (2005)

Regions	Number of provinces	Area ('000 km^2)			Population ('000)		
		Total	Average	Standard deviation	Total	Average	Standard deviation
Andalucía	8	87.60	10.95	2.87	7941.24	992.65	467.26
Aragón	3	47.72	15.91	1.25	1279.78	426.59	428.22
Asturias	1	10.60	10.60	0.00	1079.14	1079.14	0.00
Baleares	1	4.99	4.99	0.00	998.50	998.50	0.00
Canarias	2	7.45	3.72	0.48	1997.69	998.85	38.54
Cantabria	1	5.32	5.32	0.00	566.41	566.41	0.00
Castilla-La Mancha	5	79.46	15.89	2.81	1920.63	384.13	177.73
Castilla y León	9	94.22	10.47	3.04	2523.98	280.44	157.07
Cataluña	4	32.11	8.03	2.87	7091.65	1772.91	2348.30
C. Valenciana	3	23.26	7.75	2.65	4776.92	1592.31	961.56
Extremadura	2	41.63	20.82	1.34	1089.70	544.85	184.46
Galicia	4	29.58	7.39	2.22	2768.81	692.20	404.05
Madrid	1	8.03	8.03	0.00	6065.34	6065.34	0.00
Murcia	1	11.31	11.31	0.00	1357.02	1357.02	0.00
Navarra	1	10.39	10.39	0.00	598.34	598.34	0.00
País Vasco	3	7.23	2.41	0.55	2130.16	710.05	419.18
Rioja (La)	1	5.05	5.05	0.00	305.05	305.05	0.00
España	50	504.75	10.10	4.80	44490.35	889.81	1102.28

Note: Ceuta and Melilla are not included in the analysis.

Table 2 Beta convergence

Dependent variable: $\frac{1}{T} Log\left(\frac{y_{i,05}}{y_{i,85}}\right)$						
Independent Variables	Absolute convergence		Conditional convergence			
			Human capital		Agricultural GDP share	
	Coefs.	"t" statistics	Coefs.	"t" statistics	Coefs.	"t" statistics
Constant	0.036	28.25	-0.058	-2.75	0.040	16.14
$Log(y_{i,85})$	-0.017	-4.87	-0.030	-7.23	-0.024	-5.16
$Log(H_{i,85})$	-	-	0.055	4.45	-	-
$Agr_{i,85}$	-	-	-	-	-0.045	-2.08
R^2 adjusted	0.32		0.51		0.36	
Speed of convergence	1.48		2.28		1.90	
Half-life	39.6		22.8		29.0	

Note: y = per capita income; T = sample period; H = human capital; Agr = Agricultural GDP/Total GDP

Table 3 Inequality indexes

	G	T(0)	T(1)	A(0.25)	A(0.5)	A(1)	A(2)	A(50)
1985	0.1340	0.02856	0.0280	0.0070	0.0141	0.0282	0.0561	0.3478
1986	0.1361	0.02960	0.0290	0.0073	0.0146	0.0292	0.0582	0.3517
1987	0.1370	0.02984	0.0292	0.0073	0.0147	0.0294	0.0587	0.3579
1988	0.1336	0.02853	0.0280	0.0070	0.0140	0.0281	0.0562	0.3468
1989	0.1342	0.02851	0.0279	0.0070	0.0140	0.0281	0.0561	0.3464
1990	0.1307	0.02699	0.0264	0.0066	0.0133	0.0266	0.0532	0.3426
1991	0.1296	0.02636	0.0259	0.0065	0.0130	0.0260	0.0518	0.3257
1992	0.1290	0.02596	0.0256	0.0064	0.0128	0.0256	0.0508	0.3135
1993	0.1277	0.02539	0.0250	0.0063	0.0125	0.0251	0.0498	0.3159
1994	0.1323	0.02732	0.0268	0.0067	0.0135	0.0270	0.0537	0.3268
1995	0.1261	0.02507	0.0244	0.0061	0.0123	0.0248	0.0496	0.3049
1996	0.1234	0.02407	0.0235	0.0059	0.0118	0.0238	0.0476	0.2958
1997	0.1207	0.02296	0.0224	0.0056	0.0113	0.0227	0.0454	0.2932
1998	0.1201	0.02267	0.0222	0.0056	0.0112	0.0224	0.0448	0.2859
1999	0.1177	0.02178	0.0213	0.0053	0.0107	0.0215	0.0432	0.2824
2000	0.1333	0.02768	0.0274	0.0069	0.0137	0.0273	0.0538	0.3126
2001	0.1315	0.02695	0.0266	0.0067	0.0133	0.0266	0.0524	0.3066
2002	0.1268	0.02498	0.0247	0.0062	0.0124	0.0247	0.0487	0.2915
2003	0.1240	0.02391	0.0237	0.0059	0.0118	0.0236	0.0467	0.2831
2004	0.1237	0.02379	0.0236	0.0059	0.0118	0.0235	0.0464	0.2727
2005	0.1237	0.02369	0.0235	0.0059	0.0118	0.0234	0.0461	0.2687
Variation (%)	-7.71	-17.05	-16.10	-16.24	-16.43	-16.80	-17.82	-22.74

Note: G = Gini index; T = Theil index; A = Atkinson index

Table 4 Polarisation

	Bipolarisation		Tripolarisation	
	a=1	*a*=1,5	*a*=1	*a*=1,5
1985	0.097	0.069	0.081	0.047
1990	0.099	0.070	0.080	0.047
1995	0.098	0.070	0.080	0.048
2000	0.106	0.075	0.092	0.059
2005	0.098	0.069	0.081	0.049

Note: α = parameter denoting sensibility to polarisation

Table 5 Transition matrix (1985-2005)

	n	[60-75)	[75-90)	[90-110)	[110-125)	[125-175)
n	**50**	6	18	16	6	4
[60-75)	15	**33.33**	66.67	0.00	0.00	0.00
[75-90)	10	0.00	**50.00**	50.00	0.00	0.00
[90-110)	18	5.56	16.67	**55.56**	16.67	5.56
[110-125)	2	0.00	0.00	0.00	**50.00**	50.00
[125-175)	5	0.00	0.00	20.00	40.00	**40.00**

Table 6 Step-by-step transition matrix (1985-2005)

	[60-75)	[75-90)	[90-110)	[110-125)	[125-175)
[60-75)	**22.51**	53.00	21.34	2.52	0.63
[75-90)	19.51	**50.99**	24.79	3.69	1.02
[90-110)	3.43	24.19	**46.30**	18.58	7.51
[110-125)	1.95	18.13	44.96	**23.95**	11.03
[125-175)	0.35	4.95	23.77	37.29	**33.65**
Initial distribution	30.00	20.00	36.00	4.00	10.00
Final distribution	12.00	36.00	32.00	12.00	8.00
Ergodic distribution	10.53	34.25	34.58	13.81	6.83

Table 7 Spatial dependence: Moran's I statistic

Years	Moran's I	Mean	St. Dev.	z-value	Prob
1985	0.070	-0.020	0.057	1.581	0.114
1986	0.068	-0.020	0.057	1.538	0.124
1987	0.074	-0.020	0.057	1.651	0.099
1988	0.078	-0.020	0.057	1.722	0.085
1989	0.088	-0.020	0.057	1.894	0.058
1990	0.104	-0.020	0.057	2.172	0.030
1991	0.110	-0.020	0.057	2.272	0.023
1992	0.123	-0.020	0.057	2.507	0.012
1993	0.147	-0.020	0.057	2.924	0.003
1994	0.147	-0.020	0.057	2.925	0.003
1995	0.201	-0.020	0.057	3.866	0.000
1996	0.212	-0.020	0.057	4.054	0.000
1997	0.201	-0.020	0.057	3.874	0.000
1998	0.206	-0.020	0.057	3.952	0.000
1999	0.191	-0.020	0.057	3.688	0.000
2000	0.186	-0.020	0.057	3.598	0.000
2001	0.198	-0.020	0.057	3.813	0.000
2002	0.205	-0.020	0.057	3.934	0.000
2003	0.214	-0.020	0.057	4.100	0.000
2004	0.222	-0.020	0.057	4.229	0.000
2005	0.236	-0.020	0.057	4.472	0.000

Table 8 Beta convergence: spatial contrasts

Tests	Absolute convergence		Conditional convergence			
			Human capital		Agricultural GDP share	
	values	p-values	values	p-values	values	p-values
LM-ERR	4.96	0.026	8.66	0.003	1.12	0.291
LM-EL	11.53	0.001	15.58	0.000	1.01	0.315
LM-LAG	0.33	0.567	0.29	0.593	0.56	0.453
LM-LE	6.90	0.009	7.21	0.007	0.46	0.500

Note: LM-ERR = Lagrange multiplier for spatial errors; LM-EL = LM-ERR associated robust; LM-LAG = Lagrange multiplier for spatial lags; LM-LE = LM-LAG associated robust.

Table 9 Beta convergence: spatial estimation

Dependent variable: $\frac{1}{T} Log\left(\frac{y_{i,05}}{y_{i,85}}\right)$				
	Absolute convergence		Conditional convergence	
	Coefs.	"t" statistics	Coefs.	"t" statistics
Constant	0.036	15.69	-0.055	-2.98
$Log(y_{i,85})$	-0.021	-6.24	-0.034	-9.04
$Log(H_{i,85})$	-	-	0.054	4.98
λ	0.644	3.62	0.682	4.14
LIK	189.95		200.01	
AIC	-375.90		-394.01	
SC	-372.07		-388.28	
Speed of convergence	1.71		2.45	
Half-life	33.1		20.5	

Note: y = per capita income; T = sample period; H = human capital; Agr = Agricultural GDP/Total GDP; λ = spatial error coefficient; LIK = logarithm of maximum likelihood; AIC = Akaike's information criterion; SC = Schwartz criterion (SC)

Note: The provinces in same colour belong to the same region

Figure 1 **Provincial and regional map of Spain**

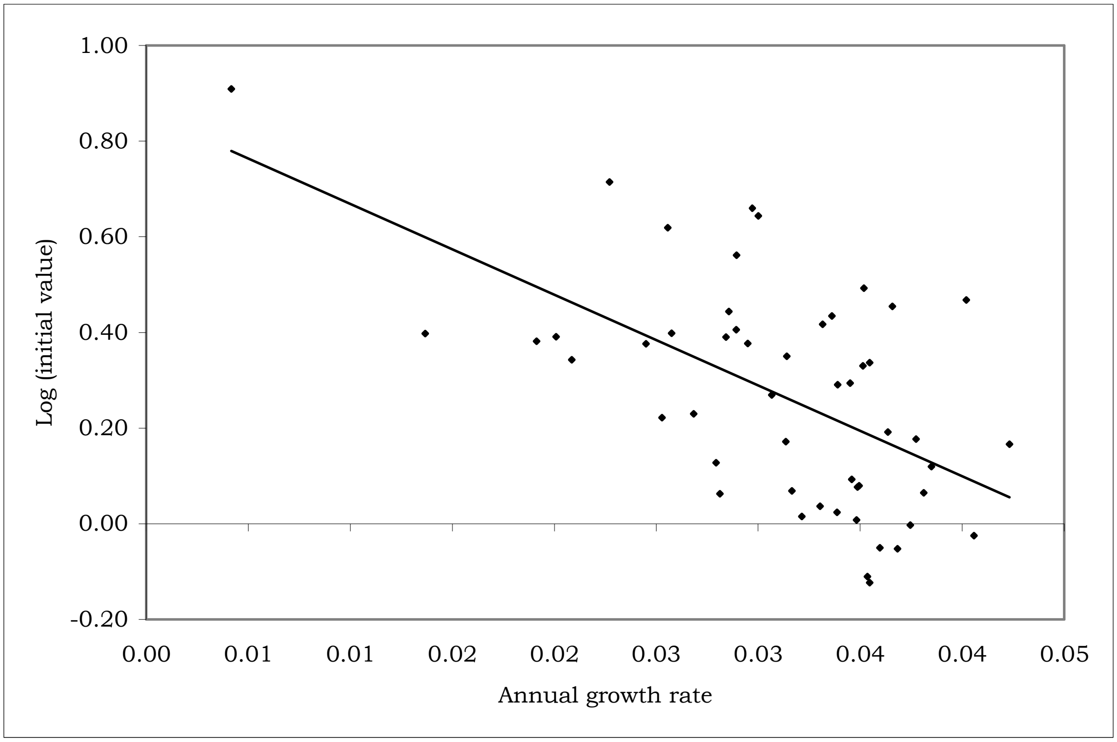


Figure 2 **β convergence**

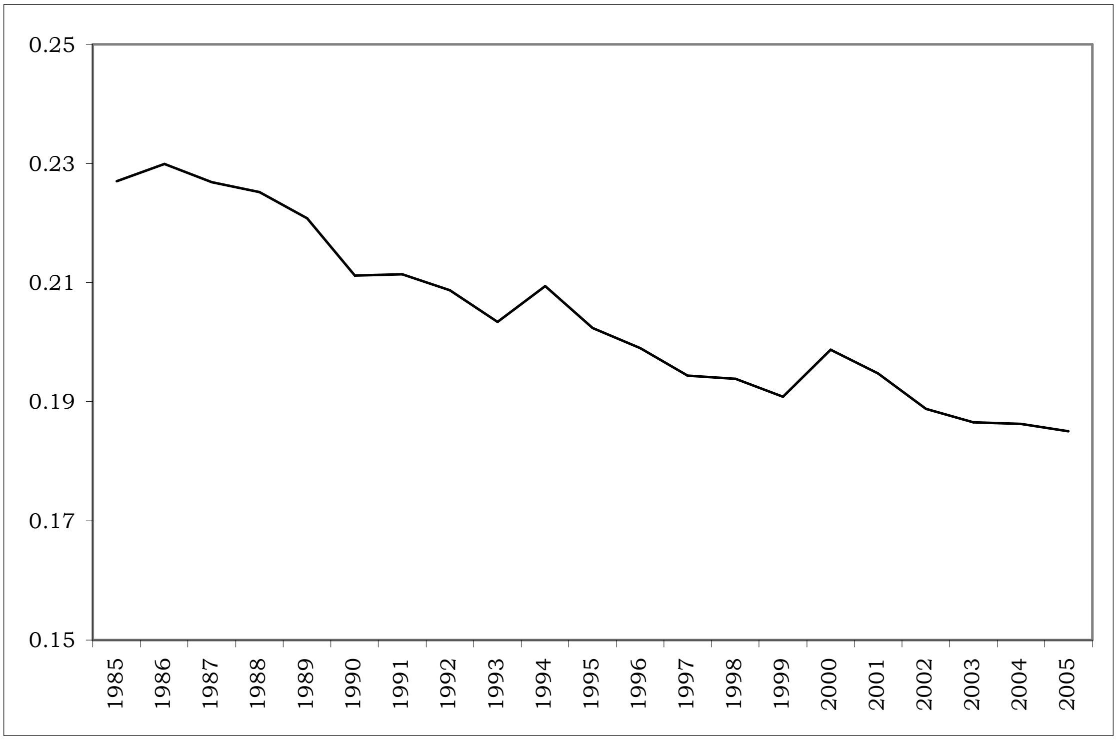


Figure 3 σ convergence

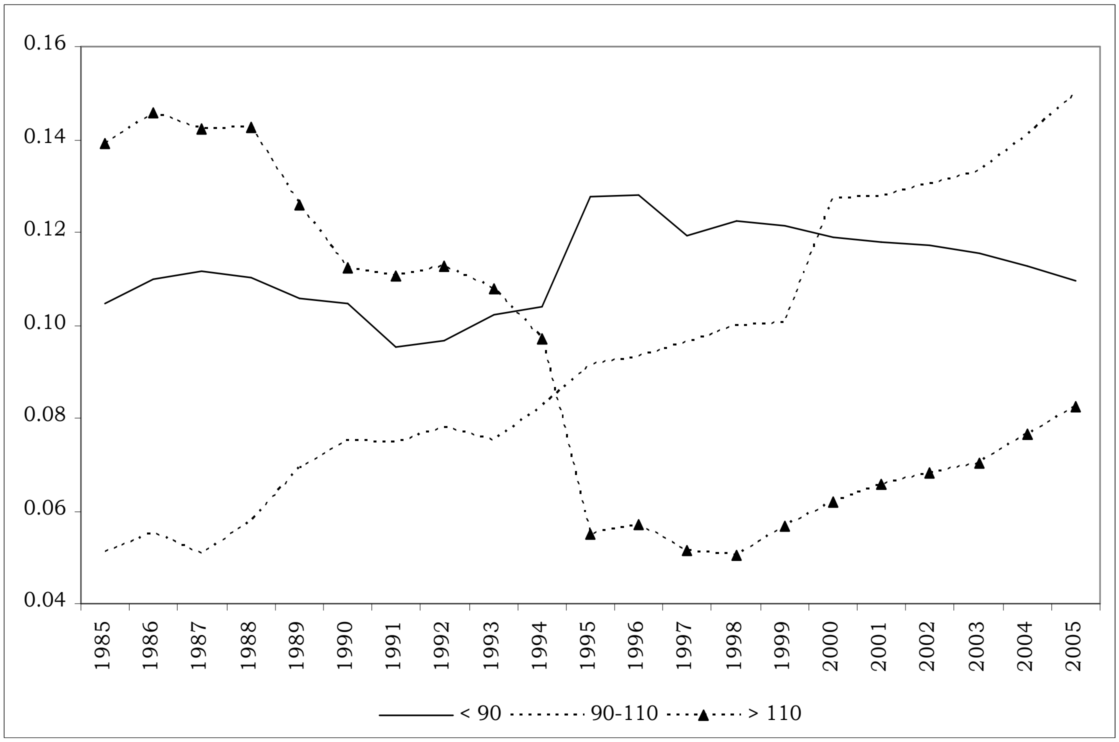


Figure 4 **σ convergence (by groups)**

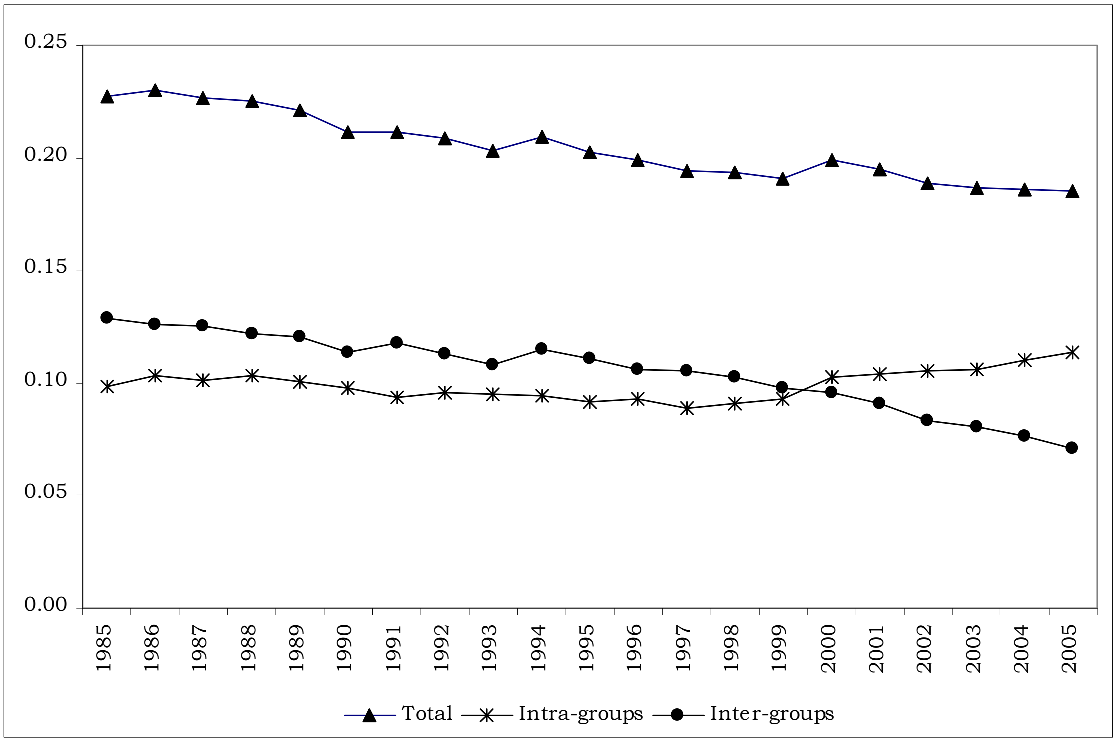


Figure 5 **σ convergence (intra e inter-groups)**

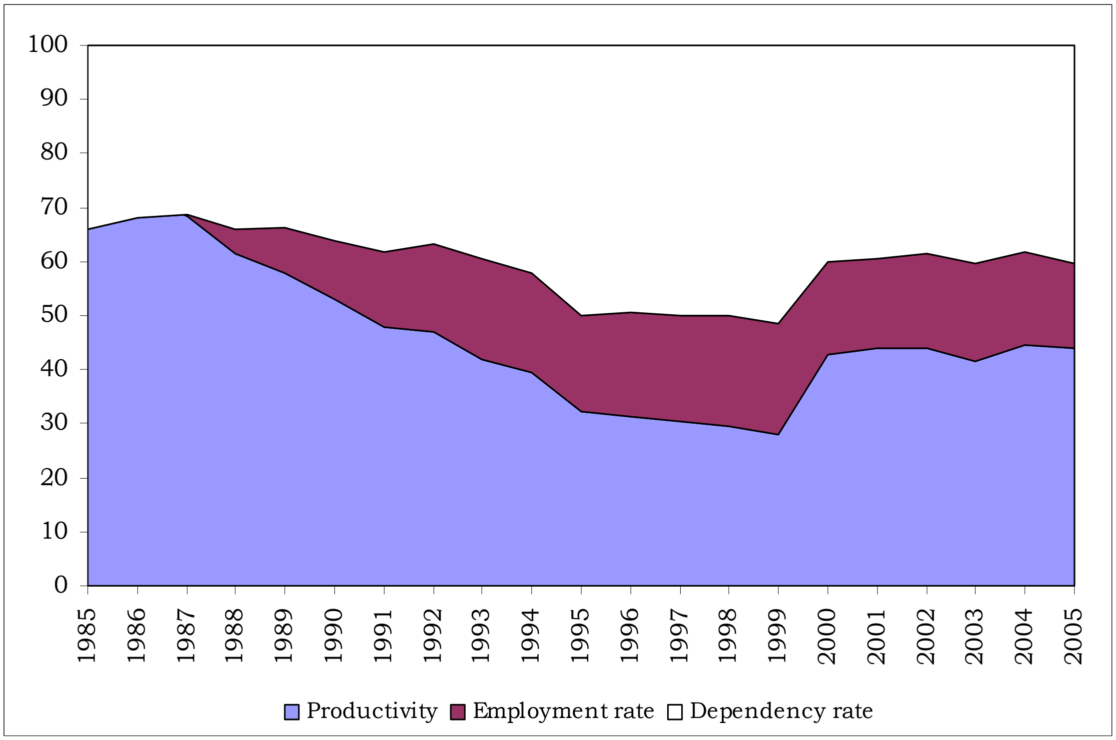


Figure 6 **Theil index. First decomposition**

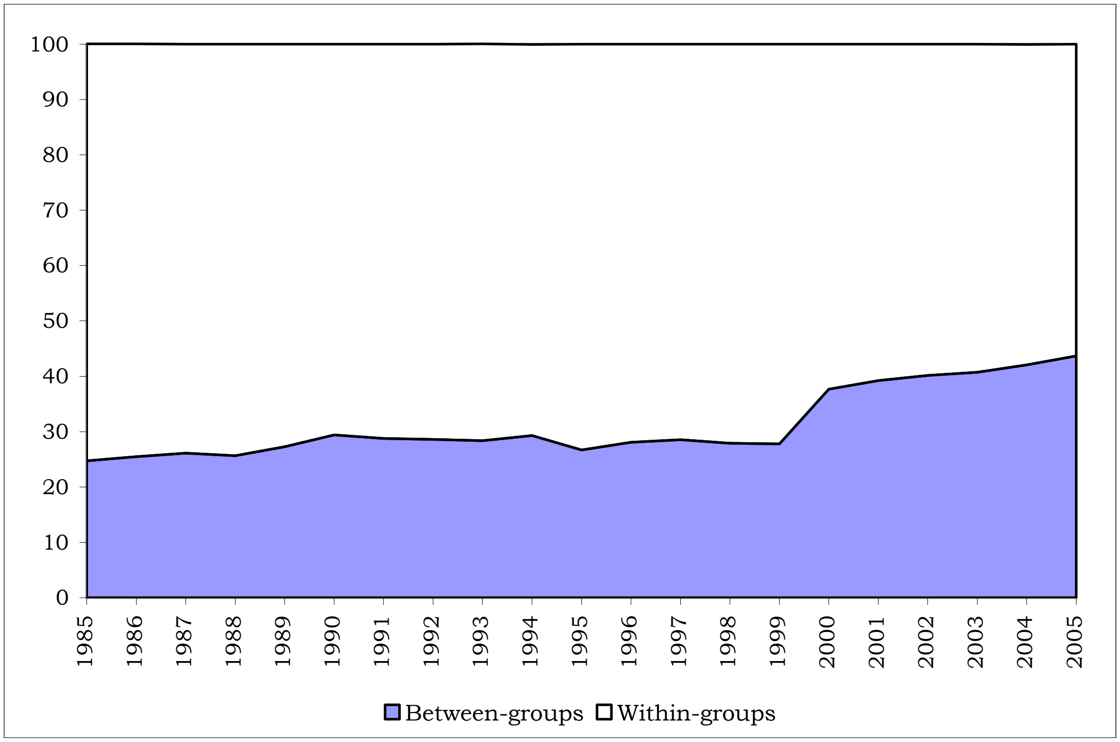
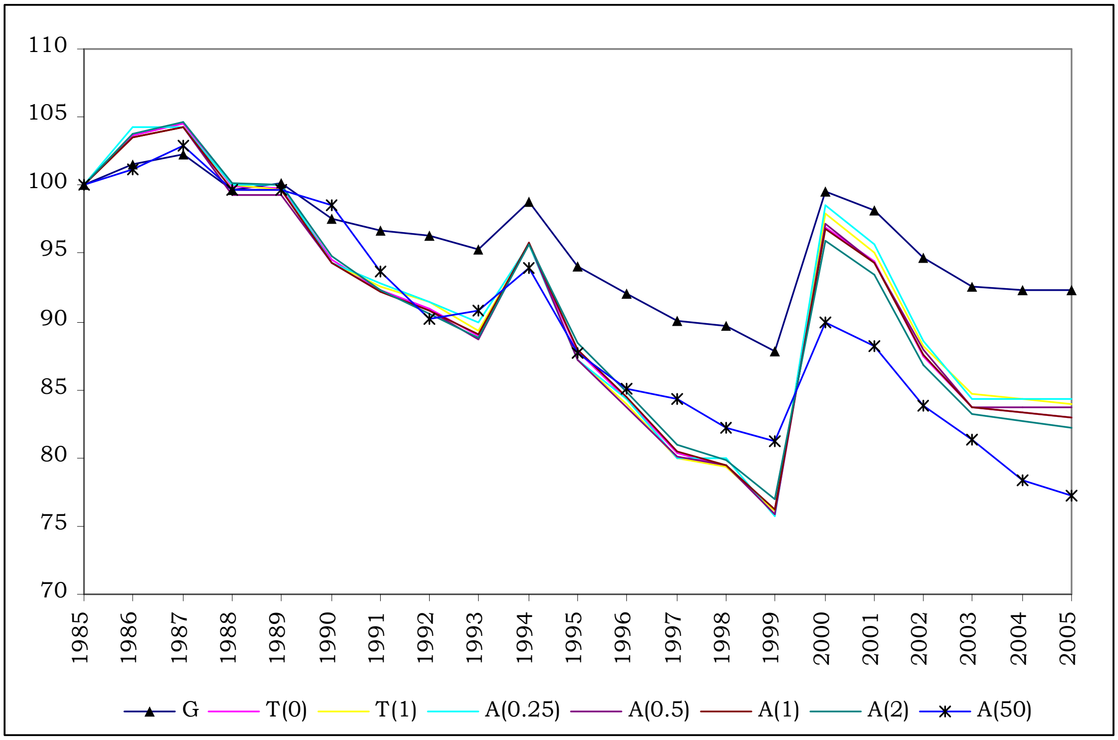
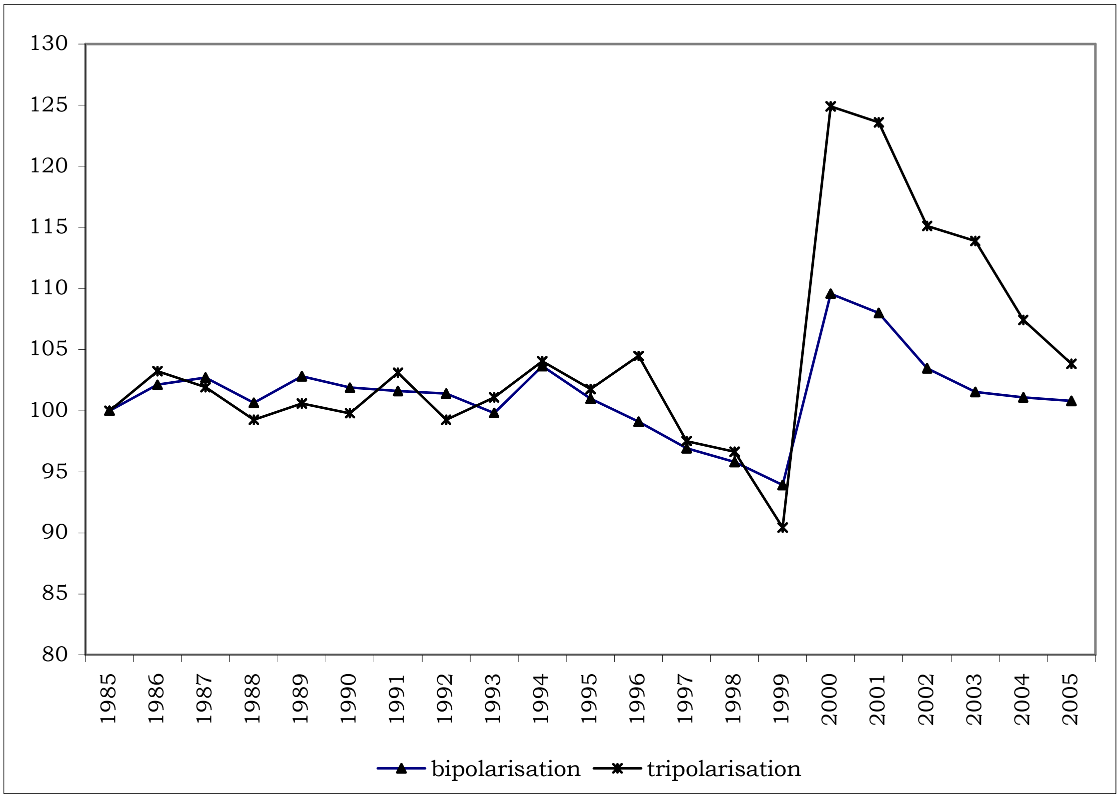


Figure 7 **Theil index. Second decomposition**



Note: G = Gini index; T = Theil index; A = Atkinson index

Figure 8 Inequality indexes



Note: Parameter denoting sensibility to polarisation *(a)* =1.5

Figure 9 Polarisation

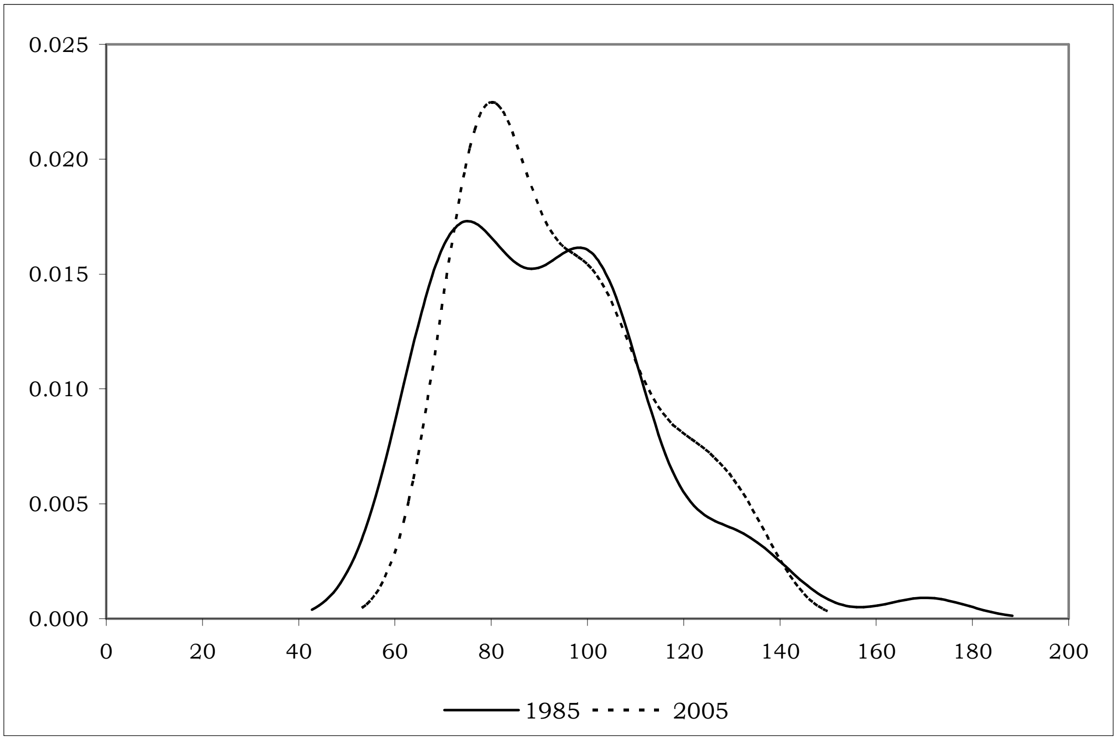


Figure 10 Density functions

Glossary of key concepts*

Convergence: a tendency of different per capita income observations to become similar or identical.

β convergence: a tendency in which low per capita income observations grow more rapidly than high per capita income ones.

σ convergence: the reduction of per capita income dispersion over time.

Density function: the function that gives the probability associated to each value of the (per capita income) distribution.

Inequality: the degree of per capita income dispersion with relation to a reference value (the average) considered to be the perfect representation of equality. Equality is a situation in which all the observations have the same per capita income.

Polarisation: the polarisation of the per capita income distribution measures the degree to which the observations of the said distribution cluster around a series of separate poles.

Spatial dependence: the coincidence of income value similarity and locational similarity. There is a positive spatial dependence when high (low) values of income tend to cluster in space. On the contrary, there is a negative spatial dependence when geographical areas tend to be surrounded by neighbours with very different income values.

Transition matrix: it is a square matrix describing the probabilities of moving from one income state to another in a dynamic system

(*) Although all these concepts are applied in our paper to provincial per capita income, they can also be applied to other variables and geographical areas.