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Convergence of EU regions Measures and evolution

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Contents

1. Introduction

The Treaty establishing the European Community defines economic and social cohesion as one of the main operational priorities of the Union. Cohesion is to be achieved mainly through the promotion of growth-enhancing conditions and the reduction of disparities between the levels of development of EU regions and Member States which are key targets of the European Cohesion Policy.

The objective of the European Cohesion Policy is defined in Articles 2 and 4 and Title XVII of the Treaty establishing the European Community. According to Article 2, Cohesion Policy should *"promote economic and social progress as well as a high level of employment, and achieve balanced and sustainable development"*. Article 158 adds, *"in particular, the Community aims to reduce the disparities between the levels of development of the different regions and the backwardness of the least favoured regions or islands, including rural areas"*.

Since the inception of the policy and the first programming period (1989-1993), this objective has often been translated as the promotion of convergence between EU regions, and in spite of the fact that Cohesion Policy aims at more than purely economic convergence, the reduction of regional disparities in the level of development has mainly been measured as the convergence of regional levels of GDP per head relative to the EU average.

This type of convergence has even become a major aspect in assessing the effectiveness of the European Cohesion Policy. Many contributions have inferred conclusions concerning the extent to which Cohesion Policy delivers results from the examination of the convergence process among EU regions, some with positive and others with negative findings. In fact, information concerning the effectiveness of the EU Cohesion Policy that can be inferred from observing the convergence of EU regions is actually extremely limited. Establishing causality indeed requires the use of appropriate counterfactuals. Nevertheless, convergence remains a key aspect of the policy and its examination is therefore essential.

However, measuring convergence presents some complexities. First, there are several definitions of convergence and although coherent, they correspond to different concepts of convergence. One should therefore have a clear view of what is measured when using convergence indices. Second, there is no convergence measure capable of capturing all relevant aspects of a convergence process. It is therefore important to know what the specificities and the limits of the existing measures are.

This paper examines convergence among EU regions using different approaches and methodologies. The objective is twofold. On the one hand, the paper conducts an update assessment of regional disparities in the EU bringing together the most frequent instruments used in the analysis of convergence and inequalities. On the other hand, the paper takes the opportunity to clarify the concepts of convergence and discuss the various measures as well as the underlying methodologies. The paper builds on both a literature review and original calculations. For the sake of concision, convergence is only examined under the dimension of GDP per head at the level of the EU NUTS 2 regions; however these methods and measures can of course be applied to other economic indicators and/or to other geographical units.

Attention must be brought to a few methodological issues. First, the smaller the geographical unit, the more likely a substantial fraction of local GDP is attributable to commuters, and the more difficult it becomes to interpret the concept of GDP per head, notably as a proxy for the regional income per head. Addressing this issue is beyond the scope of this paper, but such considerations should be kept in mind when discussing regional inequalities in terms of GDP per head. In particular, this is the reason why we do not extend the analysis to the NUTS 3 level. Second, one must be aware that inequality/disparity measures will in general be sensitive to the number of observations. This makes the comparison of disparities between areas including a different number of regions (e.g. countries) difficult and most of the time meaningless. Third, inequality measures computed on too few observations are likely to have no statistical significance. This is why the paper does not always report the analysis of regional inequalities for countries having too few regions.

The paper is structured as follows: section 2 discusses the concept of Beta (β)-convergence and reviews some of the results obtained when analysing this type of process among EU regions. Section 3 focuses on the concept of Sigma (σ)-convergence while applying related measures to EU data. Section 4 is devoted to analysing the distribution of EU regional GDP per head and its dynamics. Finally, section 5 provides concluding remarks.

2. Beta-convergence

Beta-convergence refers to a process in which poor regions grow faster than rich ones and therefore catch up on them. The concept of Beta-convergence is directly related to neo-classical growth theory (Solow, 1956) where one key assumption is that factors of production, in particular capital, are subject to diminishing return. Accordingly, the growth process should lead economies to a long-run steady-state characterised by a rate of growth which depends only on the (exogenous) rates of technological progress and labour force growth. Diminishing return also implies that the growth rate of poor economies should be higher and their income and/or GDP per head levels should catch up with those of rich economies.

When all economies are assumed to converge towards the same steady-state (in terms of GDP per head and growth rate), Beta-convergence is said to be absolute. However, the steady-state may depend on features specific to each economy, in which case convergence will still take place, but not necessarily at the same long-run levels. This will be the case when GDP per head is supposed to depend on a series of determinants such as factor endowment or institutions, which can vary from one economy to the other even in the long-run. Beta-convergence is then said to be conditional.

The seminal papers by Barro and Sala-i-Martin (1992) and Mankiw et al. (1992) have triggered a huge amount of literature attempting to empirically detect and measure the extent of Beta-convergence in various contexts. As pointed out by Sala-i-Martin (1996), one of the striking results obtained is the regularity of the estimated speed with which economies converge to their steady-state, namely around two percent a year.[1]

The methodology used to measure Beta-convergence generally involves estimating a growth equation in the following form:

$$ln(\Delta y_{i,t}) = \alpha + \beta\, ln(yi,t\text{-}1) + \gamma Z_{i,t} + u_{i,t} \qquad (1)$$

where

- $y_{i,t}$ and $\Delta y_{i,t}$ are respectively the level and the growth rate of GDP per head in region i at time t;
- $Z_{i,t}$ includes all other factors supposedly affecting the growth rate;
- $u_{i,t}$ is the standard error term; and
- α,β and $\Delta\Delta$ are the parameters to be estimated.

A negative relationship between the growth rate ($\Delta y_{i,t}$) and the initial level of GDP per head ($y_{i,t-1}$), i.e. β is significant and negative, is the sign of a convergence process. The estimated value of β also indicates the rate at which regions approach their steady-state and hence the speed of convergence. Based on this value, the so-called half-life can be computed, i.e. the time span which is necessary for current disparities to be halved. For instance, a value for β of two percent implies a half-life of 28 years.

If the value of γ is restricted to 0, absolute convergence is assumed (see for instance Cuadrado-Roura, 2001, López-Baso, 2003, Yin et al., 2003 or Geppert et al., 2005) while if it is freely estimated, conditional convergence is assumed (see for instance Neven and Gouyette, 1995, Cappelen et al., 2003, Basile et al., 2005). The same specification can be used to test the existence of a convergence process on other economic variables such as GDP per worker (labour productivity).

More recent contributions also introduce a spatial dimension into the formulation of the problem (see for instance Baumont et al., 2003 or Dall'erba and Le Gallo, 2006). There are indeed reasons to believe that the omission of a space from the analysis of the regional Beta-convergence process is likely to produce biased results. First, working with regional data indeed requires addressing the specific issue of spatial dependence. The proximity and numerous linkages between (more or less) neighbouring regions imply that regional economic variables are likely to be interdependent which conflicts with the assumptions under which equation (1) can be validly estimated. One solution consists in introducing so-called spatial lags or cross-regressive models (accounting for the fact that the growth rate of one region also depends on either the growth rate or the level of income of surrounding regions) or considering spatial error models (accounting for possible systematic measurement errors due to the spatial correlation of the variables included in the model and which make the assumption of spatial independence of the error terms too restrictive).

Second, differences in the fundamentals of regional economies introduce the possibility of spatial heterogeneity. Spatial heterogeneity means that the economic relationship represented by (1) is not stable over space which implies that the true value of its coefficients varies in space (which is referred to as structural instability) and/or that the variances-covariance of the error term varies across observations (which is referred to as groupwise heteroskedasticity). Spatial heterogeneity is related to the concept of convergence clubs, which accounts for the possibility of multiple, locally stable, steady-state equilibrium to which economies with similar fundamentals converge (Durlauf and Johnson, 1995).

Not surprisingly, the results obtained with such an approach strongly depend on the specification adopted (absolute or conditional convergence, variables included in Z, incorporation of spatial effects) and on the observations (period and regions considered, dataset used). It is therefore difficult to draw a single general conclusion from the vast panel of existing studies (see for instance the survey by Eckey and Türk, 2006).

[1] *It was never really clear what was driving this two percent result and it is even sometimes discussed as a statistical artefact. However, it keeps coming out of a large span of studies and became some sort of reference in the literature.*

However, the main messages emerging from this literature can be summarised as follows:

- a Beta-convergence process is taking place among EU regions, at both EU-15 and EU-27 level;
- the speed of convergence is not constant in time, with low values being generally found during the eighties and higher values being detected for periods before and after that decade;
- the estimated speed of convergence is rather low when absolute convergence models are used and higher when using conditional convergence models, which mostly reflects the fact that although convergence is sometimes higher within some groups of regions compared to others (e.g. core vs. periphery regions), it is often much lower between these groups;
- the inclusion of spatial effects is in general highly relevant (presence of significant local spatial autocorrelation and of spatial heterogeneity) and tends to reduce the estimated speed of the global convergence process while highlighting that the speed of convergence is higher for the poorest regions of Europe.

3. Sigma-convergence

While Beta-convergence focuses on detecting possible catching-up processes, Sigma-convergence simply refers to a reduction of disparities among regions in time. The two concepts are of course closely related. Formally, Beta-convergence is necessary but not sufficient for Sigma-convergence. Intuitively, this is either because economies can converge towards one another but random shocks push them apart or because, in the case of conditional Beta-convergence, economies can converge towards different steady-states.

This and a number of limitations of the Beta-convergence approach (see for instance Quah, 1993) have led some economists to suggest that the concept of Sigma-convergence is more revealing of the reality as it directly describes the distribution of income across economies without relying on the estimation of a particular model.

The most frequently used summary measures of Sigma-convergence are the standard deviation or the coefficient of variation of regional GDP per head. However, other indices exist and present interesting properties (see for instance Cowell, 1995 or World Bank, 1999 for a detailed review of the mathematical properties of the most popular summary inequality measures). We propose to review five measures: the coefficient of variation, the Gini coefficient, the Atkinson index, the Theil index and the Mean Logarithmic Deviation (MLD). For each of these measures, regional disparities will be evaluated at EU-15 and/or EU-27 levels in terms of their GDP per head, with regions being weighted by their population in the computations.

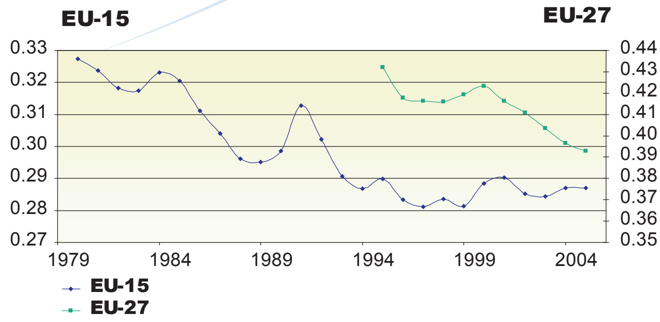
The weighting schemes and implicit welfare functions vary across measures. For example, the MLD is more sensitive to changes at the lower end of the distribution, while the coefficient of variation is responsive to changes in the upper end of the distribution. The Gini coefficient is more sensitive to changes in inequality around the median. Consequently, these measures may not rank two distributions the same way, nor will time series patterns necessarily be the same for different measures. It is therefore generally required to compute a variety of measures to draw firm conclusions about changes in the extent of disparities.

Coefficient of variation

The coefficient of variation is a normalised measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation to the mean. It is often reported as a percentage by multiplying the above calculation by 100 which is sometimes referred to as the relative standard deviation (RSD or %RSD). The coefficient of variation is often preferred to the standard deviation which has no interpretable meaning on its own unless the mean value is also reported. For a given standard deviation value, the coefficient of variation indicates a high or low degree of variability only in relation to the mean value.

The following figure shows the evolution of the coefficient of variation calculated for the EU-15 and EU-27 NUTS 2 regions for the period 1980-2005 and 1995-2005 respectively.

Figure 1: Coefficient variation: GDP per head, NUTS 2 regions, EU-15 and EU-27

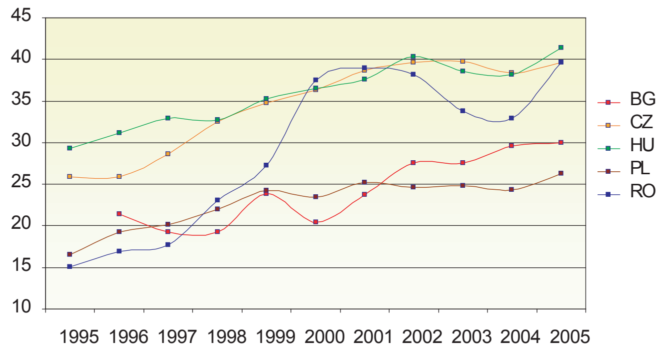


Source: Cambridge Econometrics and EUROSTAT database. DG REGIO's own calculation.

The results are in line with the findings regularly reported in the literature (see for instance Neven and Gouyette 1995, Magrini 2004 or Ertur et al. 2006). Convergence between EU-15 regions was strong up to the mid 90s, but the process since then has lost momentum. From 1980 to 1996, the evolution of disparities among EU-15 regions indeed shows a clear downward trend, the coefficient of variation decreasing from 0.33 to 0.28. On the contrary, since 1996 it has remained in a band of values between 0.28 and 0.29, its fluctuations possibly reflecting some temporary influence of the business cycle on the extent of disparities. On the other hand, disparities continue to decrease rapidly among EU-27 regions, the coefficient of variation falling from 0.43 in 1995 to 0.35 in 2005. This has led many observers to conclude that if convergence is still at work within the EU-27, it is due to the fact that the poorest regions in the new Member States are catching up on the Union's richest ones, while among EU-15 regions convergence is no longer taking place.

The fact that regional disparities decline when considering the EU as a whole does not prevent disparities from increasing within a number of Member States, in particular those that recently joined the Union. The following figure displays the evolution of the coefficient of variation calculated separately for the regions of the new Member States.

Figure 2: Coefficient variation: GDP per head, NUTS 2 regions, EU-12 countries*



** Slovenia is not included, having only two regions.*
Source: EUROSTAT database. DG REGIO's own calculation.

For all countries considered, disparities have increased, sometimes dramatically, as in Romania where the coefficient of variation rose from 0.15 in 1995 to almost 0.40 in 2005. To a large extent, such evolution stems from the fact that in each country the process of growth presents significant local differences, and is very strong in a limited number of regions which generally include the capital city region.

Gini coefficient

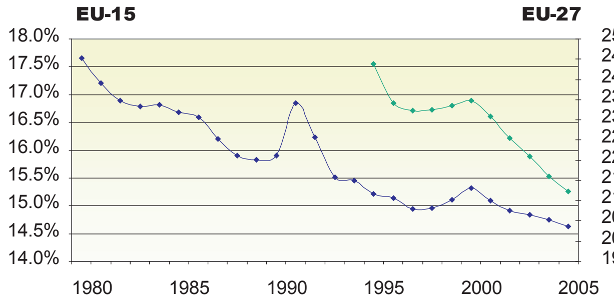
The Gini coefficient is mostly used as a measure of inequality in the distribution of personal income or wealth. By definition, it varies between 0 and 1. A low value indicates more equal distribution (0 corresponding to perfect equality), while a high Gini coefficient indicates more unequal distribution (1 corresponding to perfect inequality where income is concentrated in the hands of one individual). The Gini index is the Gini coefficient expressed as a percentage.

The Gini coefficient can be used to compare income distributions across different populations, in particular countries and regions. However, it is influenced by the granularity of the measurements. For example, a computation based on five 20% quantiles (low granularity) will usually yield a lower Gini coefficient than one based on twenty 5% quantiles (high granularity) taken from the same distribution.

The following figure shows the evolution of the Gini index calculated for EU-15 and EU-27 NUTS 2 regions for the period 1980-2005 and 1995-2005 respectively.

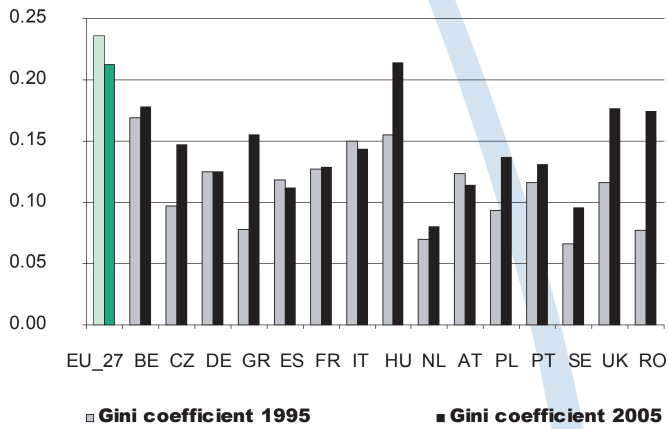
Figure 3: Gini index: GDP per head, NUTS 2 regions, EU-15 and EU-27

Source: EUROSTAT database. DG REGIO's own calculation.



Under this measure, disparities among EU-15 regions steadily declined from 17.7% in 1980 to 14.6% in 2005. Most of the reduction however took place before 1995. At the level of the EU-27, regional inequalities in GDP per head declined faster, from 24.4% in 1995 to 21.2% in 2005. Again, this observation is not incompatible with opposite trends within countries. As reflected in Figure 4, inequalities indeed increased over the same time span in a number of Member States.

Figure 4: Gini coefficients: GDP per head, NUTS 2 regions, EU-27 and within Member States, 1995-2005*



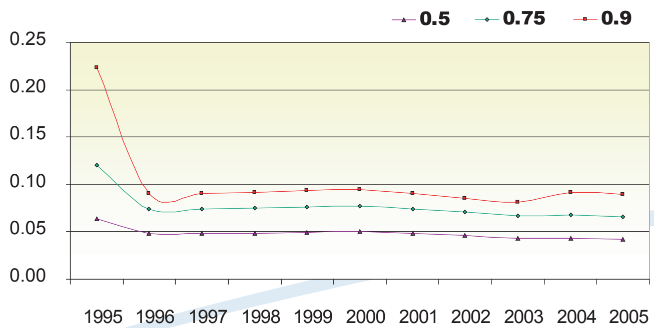
** Member States with fewer than 6 regions are not included.*
Source: EUROSTAT database. DG REGIO's own calculation.

Atkinson index

The Atkinson index is another popular measure of income inequality. Its distinguishing feature is its ability to emphasise movements in particular segments of the distribution. Specifically, a parameter entering into the computation of the index allows for giving more or less weight to changes in a given portion of the income distribution. This parameter, known as the level of "inequality aversion", is generally denoted by ε. The Atkinson index becomes more sensitive to changes at the lower end of the distribution (low income or GDP per head levels) as ε approaches 1. Conversely, as the level of inequality aversion falls, that is as ε approaches 0, the index becomes more sensitive to changes in the upper end of the income distribution.

In the following figure, the Atkinson index is computed for the EU-27 NUTS 2 regions and with three different values of the inequality aversion, 0.5, 0.75 and 0.9.

Figure 5: Atkinson index (with ε = 0.5, 0.75 and 0.9): GDP per head, NUTS 2 regions, EU-27



Source: EUROSTAT database. DG REGIO's own calculation.

The index significantly falls at the beginning of the period of observation for all values given to ε. However, the magnitude of the drop clearly increases with aversion to inequality which means that it is mostly through movements in the lower end of the distribution that inequalities reduce. In other words, the poorest regions are becoming richer rather than the richest ones becoming poorer.

Theil index

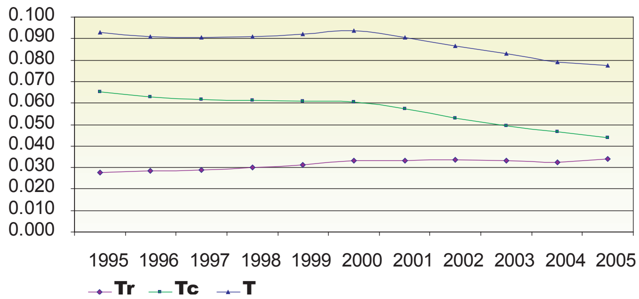
The Theil index is a particular case of the Generalised Entropy Index with coefficient 1. One interest of the Theil index compared to the preceding measures is that it corresponds to the sum of average inequality within subgroups and inequality among those subgroups, a property which is referred to as "decomposability". Formally, if the population is divided into m subgroups (e.g. Member States), if Tri is the Theil index for subgroup i (e.g. reflecting the disparities among regions of Member State i), if si is the share of group i in global income (e.g. the share of Member State i in EU GDP) and Tc the index computed on the basis of the m groups (e.g. reflecting the disparities among Member State), then the Theil index is:

$$T=\sum_{i=1}^{m} s_i T_{ri} + T_c = T_r + T_c$$

While Tc reflects the extent of disparities among the groups, Tr reflects the disparities existing within the groups. Applied to our context, the Theil index can therefore be decomposed into one capturing the extent of disparities among EU Member States and another one capturing the extent of disparities between regions within these Member States.

The following figure displays the Theil index and its decomposition into its country (Tc) and regional (Tr) components for the EU-27 NUTS 2 regions.

Figure 6: Theil index: GDP per head, NUTS 2 regions, EU-27



Source: EUROSTAT database. DG REGIO's own calculation.

The value of the index shows a reduction of disparities among EU regions which is in line with the results obtained above with other measures. However, it clearly appears that this reduction is due to the fact that disparities among Members States are strongly decreasing. On the contrary, disparities among regions within the Member States are slightly increasing. This confirms the observation already mentioned above that the reduction of regional disparities among EU countries and regions may coincide with increasing regional disparities within some countries.

The ratio Tr/T corresponds to the share of disparities explained by regional disparities within countries (referred to as intra group inequalities) while its complement Tc/T measures the share explained by disparities among Member States (referred to as inter group inequalities). Table 1 reports these shares for the period considered.

Table 1: Shares of intra and inter group inequalities, Theil index, 1995-2005

Share of T explained by:	1995	1996	1997	1998	1999	
Intra group inequalities	30%	31%	32%	33%	34%	
Inter group inequalities	70%	69%	68%	67%	66%	
Share of T explained by:	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**
Intra group inequalities	30%	31%	32%	33%	34%	35%
Inter group inequalities	65%	63%	61%	60%	59%	56%

Source: DG REGIO own calculation.

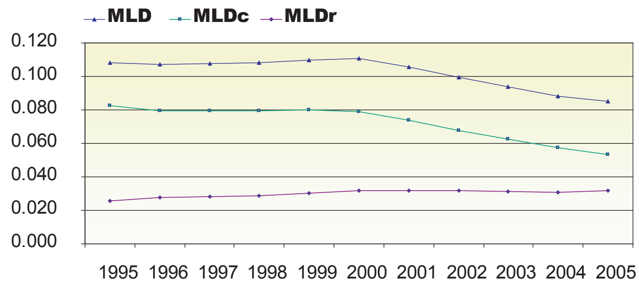
The country (inter group) component of the index clearly decreases over time. In 1995, 70% of regional disparities among EU regions reflected disparities among Member States, the remaining 30% being due to disparities between regions within Member States. By 2005, disparities among Member States accounted for only 56% of regional disparities, 44% of which are explained by regional disparities within Member States.

Mean Logarithmic Deviation

The mean logarithmic deviation (MLD) is also a member of the generalised entropy family of inequality measures, corresponding to the Generalised Entropy Index with coefficient 0. As for the Theil index, the MLD is decomposable in measures of inequality both within and between groups. However, the MLD is relatively more responsive to changes at the lower end of the distribution.

The following figure shows the MLD as well as its country (MLDc) and regional (MLDr) components for the EU-27 NUTS 2 regions.

Figure 7: MLD: GDP per head, NUTS 2 regions, EU-27



Source: EUROSTAT database. DG REGIO's own calculation.

The results are qualitatively similar to those obtained with the Theil index. Global disparities declined during the period of observation; however this process was mainly driven by a country component reflecting the reduction of disparities among EU Member States. Within countries, regional disparities slightly increased.

The contribution of the intra group and inter group inequalities to global inequalities are reported in Table 2.

Table 2: Shares of intra and inter group inequalities, MLD, 1995-2005

Share of MLD explained by:	1995	1996	1997	1998	1999	2000
Intra group inequalities	24%	26%	26%	27%	27%	29%
Inter group inequalities	76%	74%	74%	73%	73%	71%
Share of MLD explained by:		2001	2002	2003	2004	2005
Intra group inequalities		30%	32%	33%	35%	37%
Inter group inequalities		70%	68%	67%	65%	63%

Source: EUROSTAT database. DG REGIO's own calculation.

Regional disparities in the EU are increasingly less explained by disparities among the Member States, with the contribution of inter group inequalities declining from 76% to 63% between 1995 and 2005, reflecting the closing of the gap among EU countries. On the contrary, the contribution of intra group inequalities grew from 24% to 37% over the same period.

4. Analysis of the distribution

Summary measures of disparities are extremely useful as they provide a synthesis of the information and are relatively simple to compute. Their obvious drawback is that they do not allow for an in-depth look at the distribution of observations. In particular, they are not suitable for describing movements of observational units (in our case regions) within the distribution. However, such movements can add considerable insight to the analysis of regional disparities by providing more details about the mechanisms at work in the convergence process.

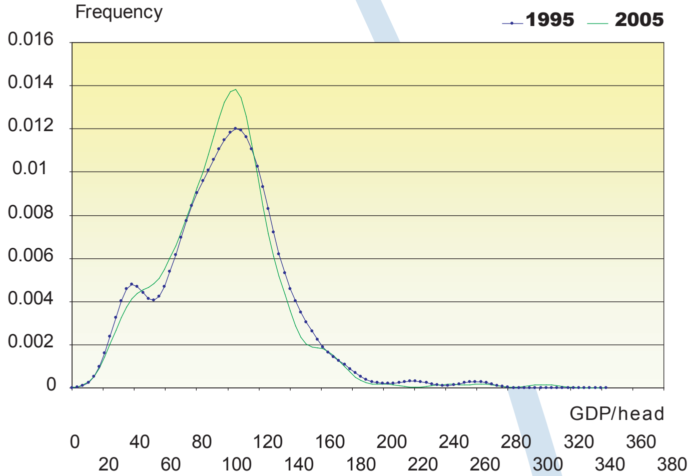
Several methods and instruments can be used to analyse the characteristics and the dynamics of the distribution. One class of instrument is based on visual inspection while others offer the possibility of deriving specific measures in order to characterise the distributions examined. For the first class, we propose to review a non-parametric estimation of density functions, cumulative density functions and Salter graphs, while for the second one, we will describe and conduct a Markov chain analysis based on transition probability matrices (see for instance Quah, 1996, Fingleton, 1997 or Overman and Puga, 2002).

Non-parametric estimation of the distribution

The most simple and frequently used non-parametric density estimator is the histogram (see for instance Boldrin and Canova, 2001). However, this instrument suffers from two severe limitations. First, histograms are not smooth, and second, they depend on end points of the sub-intervals selected to cover the data values. One way to overcome these shortcomings is to use kernel density estimators. Under this method, each data point is the centre of normalised density function, referred to as the kernel. Densities are then added vertically to produce the estimation of the distribution. If a Normal is chosen as the density function, we obtain a Gaussian (stochastic) kernel density estimation of the distribution (see for instance Barrios and Strobl, 2005).

It is of course important to select the most appropriate kernel and in particular the width of the sub-intervals surrounding the data point, referred to as the bandwidth. A common way to determine the optimal bandwidth is to choose one that minimises an optimality criterion which is often selected as the Asymptotic Mean Integrated Squared Error (AMISE). The Gaussian kernel estimation of the GDP per head distributions for the EU-27 and EU-15 NUTS 2 regions for the years 1995 and 2005 is displayed in the following figures.

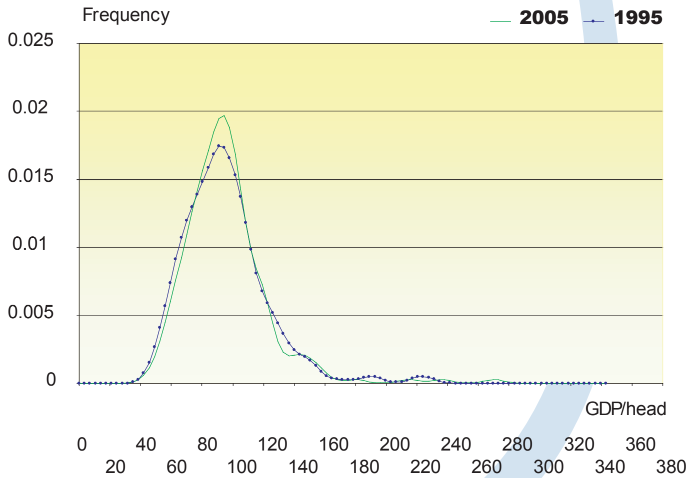
Figure 8: GDP/head (EU-27=100): Distribution EU-27 NUTS 2 regions, 1995-2005, Gaussian kernel estimation



Source: EUROSTAT database. DG REGIO's own calculation.

Figure 9: GDP/head (EU-15=100): Distribution EU-15 NUTS 2 regions, 1995-2005, Gaussian kernel estimation

Source: EUROSTAT database. DG REGIO's own calculation.



The evolution of the distributions between 1995 and 2005 indicates a convergence process at work for both the EU-15 and EU-27. Frequencies around the mean significantly increase, while they tend to decrease for values below 80% and above 120% of the EU average. In addition, for the EU-27, the estimation reveals an evolution from a bimodal to a unimodal distribution. This is particularly interesting as most analysis had indeed detected a bimodal distribution from the 1980s through to the end of the 1990s, leading to the conclusion that a polarisation process was taking place in Europe, with a "club" of poor regions converging towards a low steady-state (around 40% of the EU average in figure 8) and another club of richer regions converging towards a high steady-state (around 110% of the EU average in figure 8). The shape of the distribution in 2005 no longer shows signs of polarisation, making the scenario of various convergence clubs among EU regions less likely.

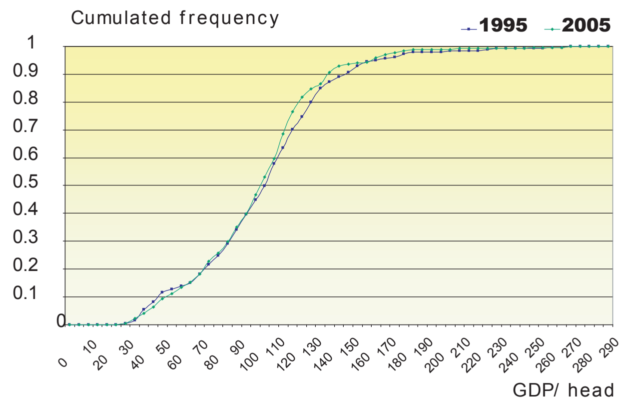
Cumulative frequency analysis

The cumulative frequency is the percentage of observational units for which the record value falls below a reference value.

For example, Figure 10 reports the cumulative frequency distributions of GDP per head for the EU-27 NUTS 2 regions in 1995 and 2005. In 1995, the cumulative frequency of the GDP/head level corresponding to 50% of the EU average was about 0.11, meaning that 11% of the observation (i.e. regions) had a GDP per head below 50% of the EU average. In 2005, this figure dropped to 8%.

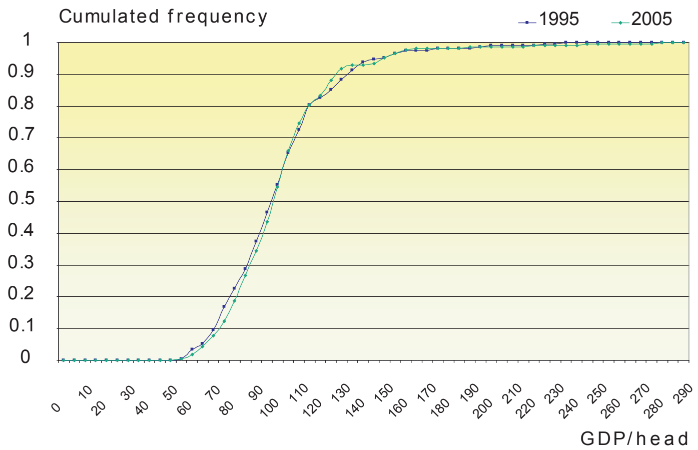
In general, the steeper the curve representing the cumulative frequency around the mean, the less the distribution features large disparities. Compared to the cumulative frequency in 1995, the frequency in 2005 is slightly steeper around 100, which confirms that convergence has taken place among EU regions between these two dates. The same type of evolution is noted when examining the cumulative frequency distributions of GDP per head for the EU-15 NUTS 2 regions (figure 11).

Figure 10: GDP/head (EU-27=100): Cumulative frequency distribution, EU-27 NUTS 2 regions, 1995-2005



Source: EUROSTAT database. DG REGIO's own calculation.

Figure 11: GDP/head (EU-15=100): Cumulative frequency distribution, EU-15 NUTS 2 regions, 1995-2005



Source: EUROSTAT database. DG REGIO's own calculation.

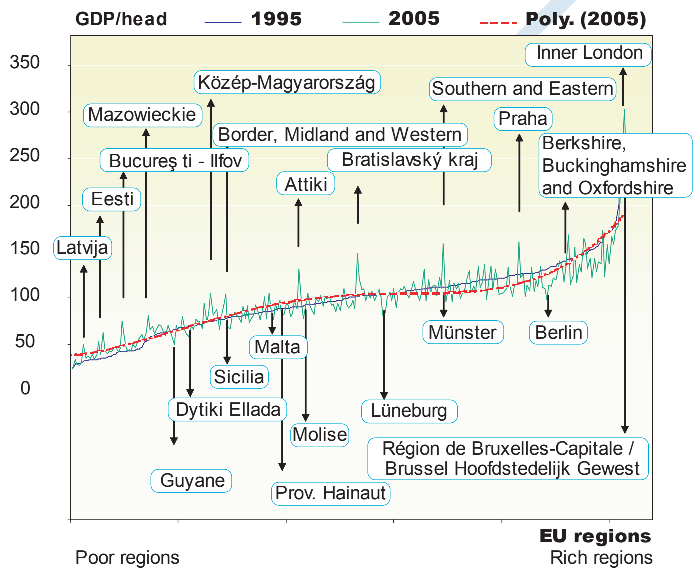
Salter graphs[2]

This method consists in ranking regions along the horizontal axis according to their GDP per head and reporting the corresponding level of GDP per head on the vertical axis for a base year. Then by holding the base year rank positions of regions constant on the horizontal axis, new series show the regions' GDP per head for subsequent years. As a result, any significant changes in the regional distribution of GDP per head become visible. In addition, regions can be identified and their performance compared.

Such graphs can be used to detect patterns of persistence or gradual change in the regional distribution of GDP per head. In particular, the more horizontal the series, the more it reflects a distribution where disparities are limited.

The following figure shows the Salter graph for the EU-27 NUTS 2 regions, comparing the distributions of their GDP per head in 1995 and 2005.

Figure 12: GDP/head (EU-27=100): Salter graph, NUTS 2 regions, 1995-2005



Source: EUROSTAT database. DG REGIO's own calculation.

An initial observation is the general tendency for the horizontality of the series to increase between 1995 and 2005, reflecting a general decrease in the extent of regional disparities. This is emphasised by comparing the 1995 series with the dashed line which is a polynomial approximation of the series for 2005. Second, the graph shows that this evolution is clearly due to a convergence process where poor regions catch up with the rich regions. The frequency of upward movements in the distribution is indeed higher in the low end of the distribution compared to that of downward movements in the high end of the distribution. Such movements are of course not uniform among poor and rich regions. Some poor regions see their relative GDP per head decline during the period (this is for instance the case for Dytiki in Greece or Hainaut in Belgium), while for some rich regions, relative GDP per head increases (e.g. Inner London).

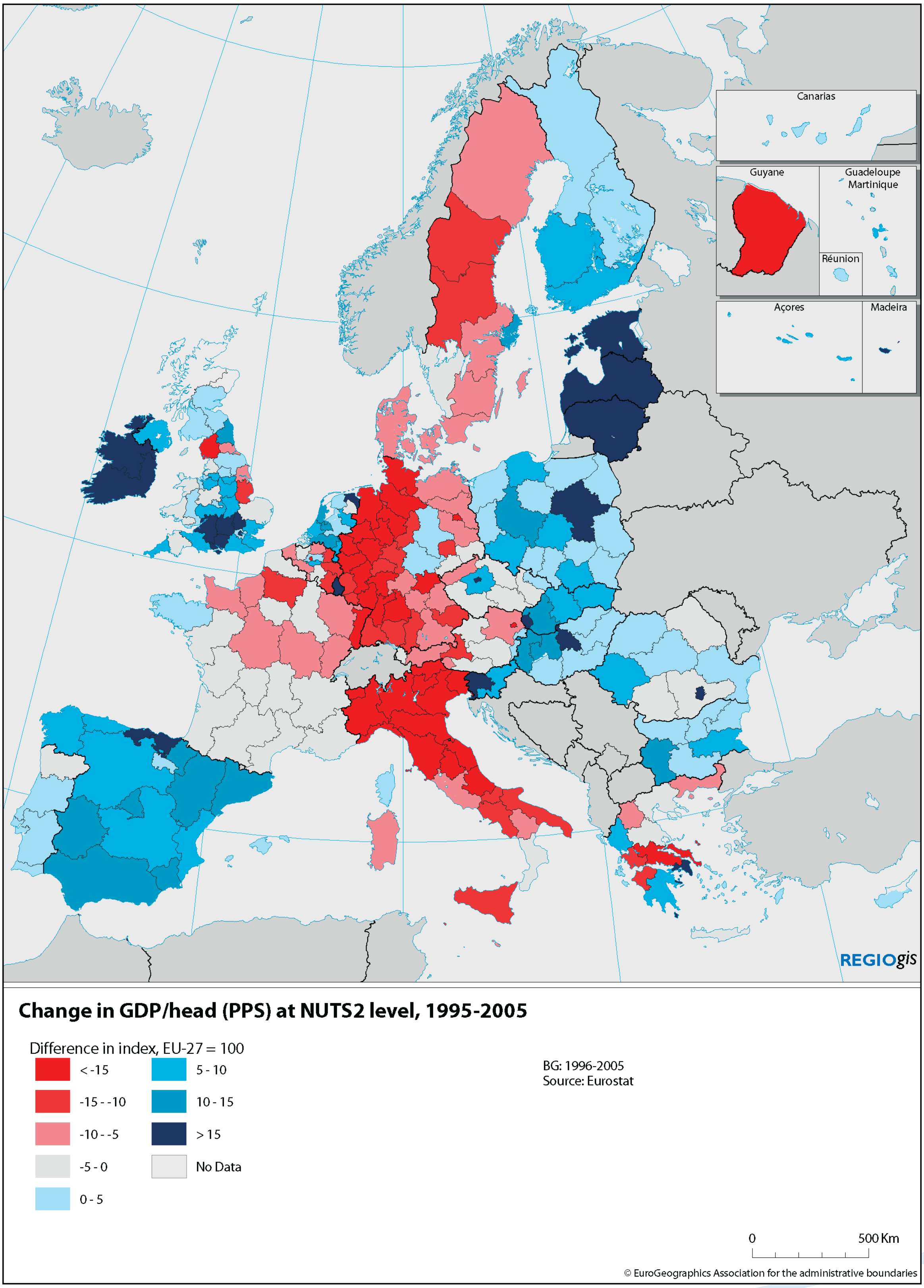
This information is conveniently complemented by mapping changes in GDP per head between 1995 and 2005.

Methods and instruments based on visual inspection of the distribution are certainly interesting for uncovering particular patterns and evolutions in the distribution of regional GDP

[2] *We are grateful to Ron Martin (University of Cambridge) for drawing our attention to the benefits of this instrument.*

per head[3]. However, they do not provide specific measures for characterising the distributions and their dynamics and therefore offer no possibility for statistical tests. From this point of view, Markov chain analysis constitutes a powerful instrument capable of detecting individual movements within the distribution and of describing its dynamics. We will provide a brief introduction to the methodology underlying Markov chain analysis and apply it to the distribution of EU regions' GDP per head.

Figure 13: GDP/head (EU-27=100): Change in GDP per head, EU-27 NUTS 2 regions, 1995-2005



[3] *For a detailed presentation of Markov chains, see Chung (1960) or Kemeny and Snell (1976).*

Let us first define a set of n non-overlapping regional GDP per head classes. The criterion on which this categorisation is based will be discussed later. For our application to the EU-27 regions, we could for instance choose n=5 and select the following classes: [0-50];]50-75];]75-100];]100-150];]150-]. Let d_{it} denote the percentage of regions in class i at time t. $d_t = (d_{1t}, \dots, d_{nt})$ is the corresponding distribution over the selected classes. In 1995, we have the following distribution:

Categories	0-50	50-75	75-100	100-150	150-
Percentage of EU-27 regions in categories	13%	12%	25%	43%	7%

Therefore in our notation, d_t = (13%, 12%, 25%, 43%, 7%) and d_{1t} = 13%. Let us now select another date, denoted by $t+^1$. We can then compute the proportion of regions belonging to category i in t and moving to category j in $t+1$. This information can be collected under the form of a transition probability matrix P. Indeed, for any two income classes i and j, the element P_{ij} defines the probability of moving from class i to j between time t and $t+1$. If for instance, we chose $t+1$ = 2005, we have the following transition probability matrix:

$$P = \begin{pmatrix} 75.8\% & 24.2\% & 0.0\% & 0.0\% & 0.0\% \\ 0.0\% & 80.6\% & 19.4\% & 0.0\% & 0.0\% \\ 0.0\% & 7.7\% & 76.9\% & 15.4\% & 0.0\% \\ 0.0\% & 0.0\% & 14.4\% & 80.2\% & 5.4\% \\ 0.0\% & 0.0\% & 0.0\% & 44.4\% & 55.6\% \end{pmatrix}$$

For instance, the value obtained for $P12$ (the element of the first row, second column) means that 24.2% of the regions which were in the class [0-50] in 1995 moved to the category]50-75] in 2005. On the other hand, $P11$ indicates that 75.8% of them remained in the same category.

The evolution of the distribution over time can be described by the following equation:

$$d_{t+1} = P\, d_t \qquad (2)$$

If we assume (i) P to be constant in time and (ii) d_{it} to be independent of its past values, then equation (2) can be analysed as a time-homogeneous Markov chain, with properties of the transition probability matrix P conveying a series of information concerning the dynamics of the distribution.

First, if P is the transition probability matrix of an ergodic Markov chain, then the chain is characterised by a stationary distribution corresponding to a steady-state towards which the distribution will converge in time[4]. This stationary distribution, which is sometimes referred to as the ergodic distribution, is an interesting element since it can be interpreted as a projection of the distribution in the future given the transition process described by P.

Second, we can derive an indicator of the speed at which the distribution is supposed to converge to this steady-state. This can for instance be expressed as the half-life of the chain, i.e. the amount of time it will take to cover half the distance separating the current distribution from the stationary distribution. The half-life is defined as:

$$\text{Half-life} = \frac{-\,Log^2}{-\,Log|\lambda_2|}$$

where λ_2 is the second eigenvalue[5] of matrix P. A high value of the half-life indicates a rapid convergence to the steady-state.

The speed of the transition process may also be examined by assessing how long it takes to transit from a state i to another state j. In Markovian terminology, this is called the mean first passage time. It is represented by an $n \times n$ matrix MP whose element ij is the average time needed to move from class i to class j.

Third, the matrix also provides information on the stability of the process, i.e. the probability of remaining in the same class. Pellegrini (2002) proposes the following stability index for the transition matrix P of dimension n:

$$S = Tr(P)/n$$

where $Tr(P)$ is the trace of P, i.e. the sum of the elements of the main diagonal. A high value of S indicates a stable process, i.e. one for which the chances to move from one category to another are small.

Finally, Pellegrini (2002) also proposes a convergence index indicating the probability that movement from the original distribution to the final one is in the direction of an increasing convergence toward the mode of the stationary distribution. The index is computed by comparing the sum of the probability value of cells in the matrix modal column and in the cells included between this column and the main diagonal from one side and the opposite diagonal from the other side to the sum of probabilities in the whole matrix. The higher the value for this index, the lower the dispersion in the final distribution and the less likely a long-run distribution characterised by polarisation on several modes will occur.

Applying these concepts to our example yields the following results:

[4] A Markov chain is ergodic if it is possible to go from every state (distribution) to any other state in a finite number of steps. Ergodicity and the existence of a stationary distribution is ensured when the modulus of the second eigenvalue of the transition matrix is strictly smaller than 1.

[5] Eigenvalues are a set of special scalars associated with a linear system of equations (that can always be written using a matrix). If the system of equations represents the evolution of an object (here a distribution) in time, eigenvalues convey information concerning its dynamics (e.g. existence of a steady-state, speed of convergence…)

Table 3: GDP/head (EU-27=100): Transition probability matrix, EU-27 NUTS 2 regions, 1995-2005[6]

Transition probability matrix							
			2005				
	GDP/head	Percentage of regions	0-50	50-75	75-100	100-150	150-
1995	0-50	13%	75.8%	24.2%	0.0%	0.0%	0.0%
	50-75	12%	0.0%	80.6%	19.4%	0.0%	0.0%
	75-100	25%	0.0%	7.7%	76.9%	15.4%	0.0%
	100-150	43%	0.0%	0.0%	14.4%	80.2%	5.4%
	150-	7%	0.0%	0.0%	0.0%	44.4%	55.6%

Summary statistics					
	0-50	50-75	75-100	100-150	150-
Stationary distribution	0%	15%	39%	41%	5%
Half-life	3.9 periods				
S	0.74				
$C_{100-150}$	0.40				
C_{75-100}	0.36				

Mean first passage time					
	0-50	50-75	75-100	100-150	150-
0-50	$9.01 * 10^{15}$	4.13	9.29	18.38	61.10
50-75	$3.72 * 10^{16}$	6.53	5.17	14.25	56.97
75-100	$3.72 * 10^{16}$	28.56	2.59	9.08	51.81
100-150	$3.72 * 10^{16}$	36.34	7.78	2.43	42.72
150-	$3.72 * 10^{16}$	38.59	10.03	2.25	19.99

Source: EUROSTAT database. DG REGIO's own calculation.

The transition probability matrix indicates a relative persistence of the distribution. The values on the diagonal are quite high, suggesting a high probability of remaining in the same class of GDP per head. This is summarised by stability index *S* which takes the value of 0.74. However, persistence is less pronounced at the end classes of the distribution. In particular, 24.2% of the poorest regions in 1995 moved up to the next category in 2005, while 19.4% of the regions in class [50-75] in 1995 moved to class [75-100] in 2005. In general, for regions with GDP per head lower than 100% of the EU average, movements towards upper categories are much more frequent than movements down, the reverse being true for regions with GDP per head above this threshold.

This shows a convergence process where poorer regions catch up on the richer ones, the distribution evolving towards one with lower frequencies at the tails, as clearly indicated by the stationary distribution. The distribution is therefore likely to feature fewer disparities in the long-run with a concentration of observations in the central categories. This is confirmed by the convergence index, measuring the probability of staying or moving to a cell that increases convergence (0.40 for convergence towards the class [100-150]; 0.36 for convergence towards the class [75-100]).

However, convergence towards the stationary distribution is rather slow with a half-life of 3.9 periods of 10 years. The thickness of the system is also well captured by the mean first passage time. The elements outside the main diagonal of MP indicate that the transitions to other categories are relatively slow, the lower passage time being 4.13 periods from class [0-50] to class [50-75]. However, the pace of transition is systematically higher for low GDP per head classes, while movements up are generally faster than movements down.

These results are in line with the convergence process that was detected at the level of the EU-27 regions using the summary measures described in the preceding section. On the contrary, while the analysis of disparities among the EU-15 based on summary measures led to the conclusion that the convergence process had come to an end by the mid 1990s, the examination of the distribution reveals important movements that the first type of measures failed to detect. Markov chain analysis conducted on the EU-15 regions is summarised in the following table.

[6] *In the case of the EU-15, the first category had to be set to [0-60] for having enough observations in this range of GDP per head. .*

Table 4: GDP/head (EU-15=100): Transition probability matrix, EU-15 NUTS 2 regions, 1995-2005[7]

Transition probability matrix							
			2005				
	GDP/head	Percentage of regions	0-60	60-75	75-100	100-150	150-
1995	0-60	5%	54.5%	45.5%	0.0%	0.0%	0.0%
	60-75	17%	8.3%	52.8%	38.9%	0.0%	0.0%
	75-100	43%	0.0%	6.7%	76.4%	16.9%	0.0%
	100-150	31%	0.0%	0.0%	24.6%	73.8%	1.5%
	150-	3%	0.0%	0.0%	0.0%	14.3%	85.7%

Summary statistics					
	0-60	60-75	75-100	100-150	150-
Stationary distribution	0%	15%	39%	41%	5%
Half-life	4.5 periods				
S	0.69				
$C_{100-150}$	0.43				
C_{75-100}	0.40				

Mean first passage time					
	0-60	60-75	75-100	100-150	150-
0-60	61.78	2.20	5.24	12.39	191.80
60-75	133.72	11.33	3.04	10.19	189.60
75-100	159.81	26.08	1.96	7.15	186.56
100-150	164.31	30.58	4.50	2.87	179.41
150-	171.31	37.58	11.50	7.00	26.63

Source: EUROSTAT database. DG REGIO's own calculation.

The persistence of the distribution is less than when taking the EU-27 regions into account. The stability index *S* is only 0.69 which is mainly explained by the low values observed on the diagonal for the lower GDP per head classes and significant movements to upper categories. Indeed, 45.5% (respectively 38.9%) of the regions in the class [0-60] (respectively [60-75]) moved to the next class over the period 1995-2005. The stationary distribution shows that while most of the convergence has already taken place for the classes of GDP per head above 75% of the EU average, the process is still underway for the lower classes and is expected to continue in the future. The convergence index is 0.43 for the class [100-150] and 0.40 for the class [75-100]).

Convergence towards the stationary distribution is even slower than for the EU-27 with a half-life of 4.5 periods. However, for low GDP per head categories, transitions are faster, the lower passage time being 2.2 periods from the class [0-60] to the class [60-75]. As for the EU-27, movements up are faster than movements down.

The results of the Markov chain analysis indicate that, although at a slow pace, a convergence process has definitely taken place among EU-15 regions for the period considered. This tendency is however not captured by the aggregate inequality measures reviewed in the preceding section. The explanation is that the number of regions in the lower categories is relatively small and even if, within the EU-15, poor regions are rapidly catching up, their weight is too small for this movement to be reflected in summary measures.

The dynamics of the transition is not necessarily constant in time and different periods of time may be characterised by more or less rapid movements taking place within the distribution. One way to examine this issue is to decompose the period of examination in different sub-periods and check if the dynamics of the system changes from one sub-period to the other. We therefore complete the analysis by considering the two sub-periods 1995-2000 and 2000-2005. The following table displays the summary statistics obtained for the respective transition probability matrices.

[7] Quah (1993) or Legallo (2004) rely on a different method for computing the transition probability matrix where cell ij is the number of occurrences of passages from class i to class j during the whole period of observation. This has the advantage of exploiting the panel dimension of the data and of giving a more precise estimation of the true transition probabilities. Adopting this approach did not lead to substantial differences in the results presented here and we therefore chose to measure transition between the two end dates of the period of observation as it makes it easier to interpret the transition probability matrix.

Table 5: GDP/head (EU-27=100): Transition probability matrix, Summary statistics, EU-27 NUTS 2 regions, 1995-2000 and 2000-2005

Summary statistics transition 1995-2000					
	0-50	50-75	75-100	100-150	150-
Stationary distribution	0%	28%	44%	25%	3%
Half-life	8.4 periods				
S	0.86				
C_{75-100}	0.29				
$C_{100-150}$	0.28				
Summary statistics transition 2000-2005					
	0-50	50-75	75-100	100-150	150-
Stationary distribution	0%	11%	33%	50%	5%
Half-life	5.8 periods				
S	0.85				
C_{75-100}	0.28				
$C_{100-150}$	0.30				

Source: EUROSTAT database. DG REGIO's own calculation.

Movements within the distribution accelerated during the period of observation. Although the stability index is identical between the two sub-periods, the speed of the convergence process is higher for the second sub-period, with a half-life of 5.8 for the sub-period 2000-2005 against a half-life of 8.4 for the sub-period 1995-2000.

The same exercise conducted for the EU-15 regions yields the following results.

Table 6: GDP/head (EU-15=100): Transition probability matrix, Summary statistics, EU-15 NUTS 2 regions, 1995-2000 and 2000-2005

Summary statistics transition 1995-2000					
	0-60	60-75	75-100	100-150	150-
Stationary distribution	8%	17%	41%	28%	6%
Half-life	6.7 periods				
S	0.79				
C_{75-100}	0.29				
Summary statistics transition 2000-2005					
	0-60	60-75	75-100	100-150	150-
Stationary distribution	0%	11%	33%	50%	5%
Half-life	5.4 periods				
S	0.8				
C_{75-100}	0.35				

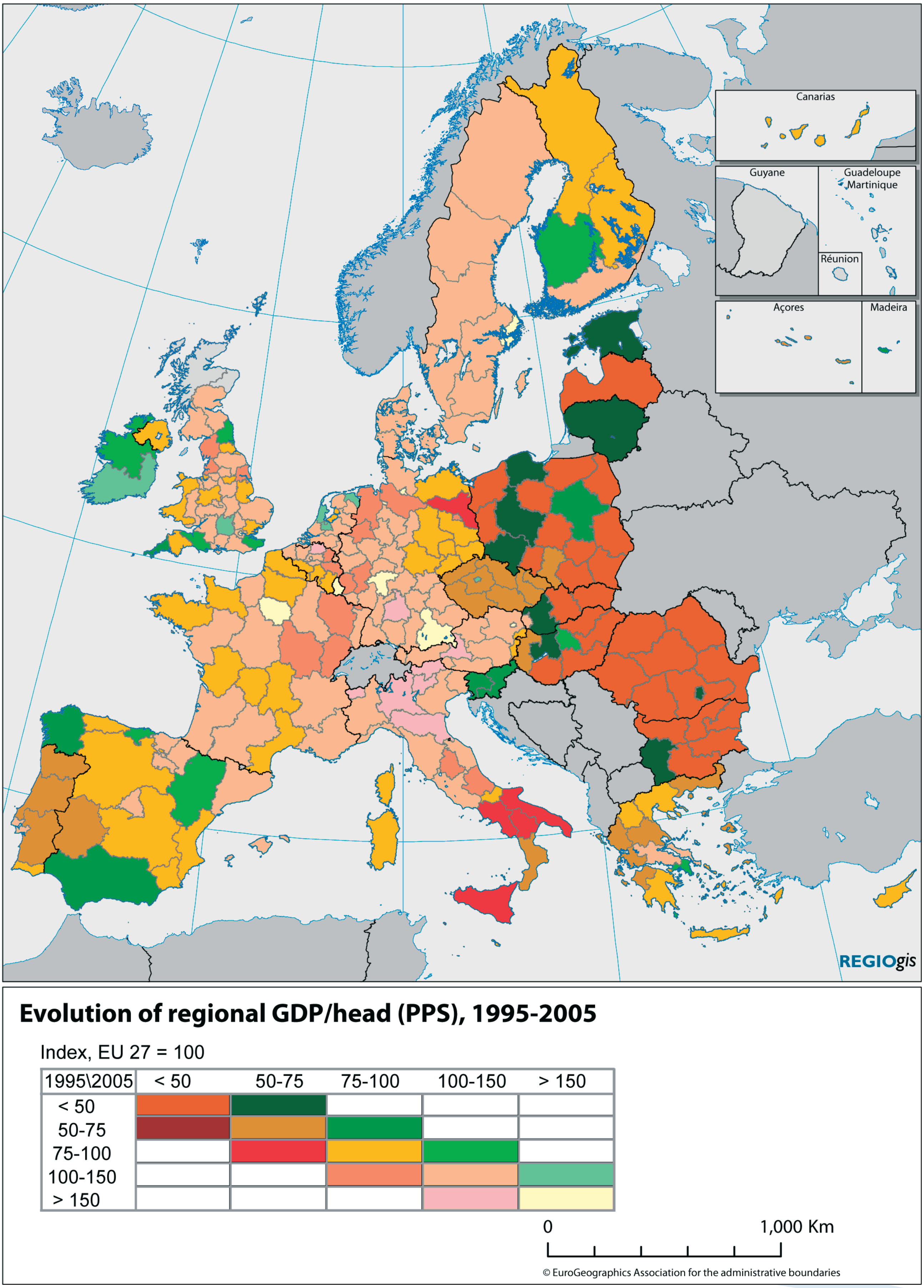
Source: EUROSTAT database. DG REGIO's own calculation.

The conclusions are qualitatively similar for the EU-15 regions although the speed of the convergence process is, as expected, relatively more stable.

Transition probability matrices allow for identifying which regions are moving and in which categories. For instance, the EU-27 regions moving from the [0-50] class to the]50-75] class between 1995 and 2005 are the following: Estonia, Lithuania, Közép-Dunántúl (Hungary), Wielkopolskie (Poland), Dolnośląskie (Poland), Pomorskie (Poland), Bucureşti – Ilfov (Romania) and Západné Slovensko (Slovakia).

Figure 14 maps movements within EU-27 regions between 1995 and 2005. Regions are identified according to three fundamental transition regimes: upwardly mobile (green), stationary (orange) and downwardly mobile (red). The category of GDP per head in 1995 is also represented, darker tones indicating lower categories of GDP per head in 1995.

Figure 14: GDP/head (EU-27=100): Mapping of transition, EU-27 NUTS 2 regions, 1995-2005



The map reveals the predominance of regions in the stationary regime. It also shows that regions in the upwardly (respectively downwardly) mobile regime are mainly poor (respectively rich) regions which demonstrates that convergence is indeed driven by a catching-up process. Notable exceptions are some regions of Southern Italy and Brandenburg-Nordost in Germany which moved from the [75-100] class to the [50-75] class.

Results of Markov chain analysis are heavily dependent on the discrete approximation of the range of values into the *n* non-overlapping classes. The choice of the classes indeed uniquely determines the transition matrix *P* and hence the entire set of results. In order to overcome such a problem, some authors (see for instance Quah, 1997) have relied on a methodology which estimates the beginning and end of period distributions by means of a stochastic kernel. The evolution of the distribution is then analysed based on a visual inspection of the three-dimensional plot of the kernel; however no specific measures characterising the dynamics can be derived from this method.[8] As an alternative, the preference is sometimes to define the classes using the *n* quantiles so that each class includes the same number of observations. The definition of the classes is then less arbitrary. As an example, the following tables report the results obtained following this approach for the EU-15.

Table 7: GDP/head (EU-15=100): Transition probability matrix, EU-15 NUTS 2 regions, 1995-2005

Transition probability matrix							
			2005				
	GDP/head	**Percentage of regions**	**0-68.6**	**68.6-90.7**	**90.7-106.7**	**106.7-124.9**	**124.9-**
1995	0-68.6	20%	66.7%	31.0%	2.4%	0.0%	0.0%
	68.6-90.7	20%	12.2%	63.4%	19.5%	2.4%	2.4%
	90.7-106.7	20%	0.0%	23.8%	35.7%	35.7%	4.8%
	106.7-124.9	20%	0.0%	2.4%	31.7%	43.9%	22.0%
	124.9-	20%	0.0%	0.0%	2.4%	26.2%	71.4%

Summary statistics					
	0-68.6	**68.6-90.7**	**90.7-106.7**	**106.7-124.9**	**124.9-**
Stationary distribution	23%	25%	26%	17%	9%
Half-life	5.3 periods				
S	0.62				
$\mathbf{C_{90.7\text{-}106.7}}$	0.34				

Mean first passage time					
	0-68.6	**68.6-90.7**	**90.7-106.7**	**106.7-124.9**	**124.9-**
0-68.6	12.66	3.84	9.26	13.05	20.27
68.6-90.7	34.13	4.63	6.74	10.39	17.54
90.7-106.7	45.95	11.82	4.92	5.70	13.80
106.7-124.9	50.06	15.94	5.37	3.93	10.34
124.9-	53.22	19.10	8.42	3.97	4.04

Source: EUROSTAT database. DG REGIO's own calculation.

A quick check reveals that the results are not qualitatively different from those obtained with the categories previously chosen[9].

The analysis of disparities based on geographical units makes sense in a series of contexts. For instance, regions are the main focus of the EU Cohesion Policy and it is therefore legitimate for EU policy analysts to examine the relative position of EU regions in relation to one another. However, the main concern of the policy remains human welfare and in such a context, as underlined by Sala-i-Martin (2006), the analysis based on geographical units may be less relevant if those units have different population sizes. Neglecting this aspect indeed amounts to down-weighting the well-being of citizens living in units with large populations. To cope with this issue, the analysis must be conducted by giving weights to regions according to their population. Tables 8 and 9 report the results of the Markov chain analysis based on this approach, respectively for the EU-27 and EU-15. Each cell of the matrix now represents percentages of the population. Table 8 for instance indicates that the population living in regions with GDP per head below 50% of the EU average in 1995 accounted for 15% of the EU-27 population. Among those citizens, 73% live in regions that remained in the same category while 27% live in regions that moved up to the next category by 2005.

[8] The sensitivity to the categories chosen is referred to as granularity.

[9] The same is true if a large number of narrower categories is used, as the characterisation of the dynamics mostly relies on the use of the eigenvalues of the transition probability matrix which becomes difficult to compute for more than six categories.

Table 8: GDP/head (EU-27=100): Transition probability matrix, EU-27 NUTS 2 regions, 1995-2005

Transition probability matrix							
			2005				
	GDP/head	Percentage of population	0-50	50-75	75-100	100-150	150-
1995	0-50	15%	73.0%	27.0%	0.0%	0.0%	0.0%
	50-75	10%	0.0%	65.3%	34.7%	0.0%	0.0%
	75-100	21%	0.0%	17.2%	66.5%	16.3%	0.0%
	100-150	44%	0.0%	0.0%	11.6%	83.5%	4.9%
	150-	10%	0.0%	0.0%	0.0%	41.3%	58.7%

Summary statistics					
	0-50	50-75	75-100	100-150	150-
Stationary distribution	0%	16%	33%	46%	5%
Half-life	3.6 periods				
S	0.69				
$C_{100-150}$	0.43				
C_{75-100}	0.36				

Mean first passage time					
	0-50	50-75	75-100	100-150	150-
0-50	$4.50*10^{15}$	3.71	6.59	15.76	58.01
50-75	$1.67*10^{16}$	6.20	2.88	12.05	54.31
75-100	$1.67*10^{16}$	15.01	3.07	9.17	51.42
100-150	$1.67*10^{16}$	24.67	9.66	2.18	42.25
150-	$1.67*10^{16}$	27.09	12.09	2.42	18.43

Source: EUROSTAT database. DG REGIO's own calculation.

Table 9: GDP/head (EU-15=100): Transition probability matrix, EU-15 NUTS 2 regions, 1995-2005

Transition probability matrix							
			2005				
	GDP/head	Percentage of population	0-50	50-75	75-100	100-150	150-
1995	0-50	6%	58.8%	41.2%	0.0%	0.0%	0.0%
	50-75	16%	4.9%	51.5%	43.6%	0.0%	0.0%
	75-100	42%	0.0%	9.1%	77.5%	13.3%	0.0%
	100-150	32%	0.0%	0.0%	26.3%	71.7%	2.0%
	150-	4%	0.0%	0.0%	0.0%	26.1%	73.9%

Summary statistics					
	0-50	50-75	75-100	100-150	150-
Stationary distribution	1%	12%	56%	28%	2%
Half-life	2.6 periods				
S	0.67				
$C_{100-150}$	0.44				
C_{75-100}	0.43				

Mean first passage time					
	0-50	50-75	75-100	100-150	150-
0-50	70.76	2.43	5.00	14.26	185.64
50-75	169.47	8.51	2.57	11.83	183.21
75-100	186.43	16.96	1.78	9.26	180.64
100-150	190.52	21.05	4.10	3.51	171.38
150-	194.36	24.89	7.93	3.83	45.69

Source: EUROSTAT database. DG REGIO's own calculation.

Results are qualitatively similar to those obtained on the basis of geographical units. However we can see that the speed of the convergence process with EU-15 regions is slightly higher when using a population basis. This simply reflects the fact that movements towards the stationary distribution have on average been more frequent for regions with relatively large populations.

Finally, recent contributions have introduced a spatial dimension into Markov chain analysis of regional disparities (see Rey, 2001, Legallo 2001 or Janikas and Rey, 2005). The objective is to account for the possibility that the transition of a particular region is influenced by its location and in particular the performance of its neighbours. Upward movements can for instance be hampered (favoured) by being located within a relatively depressed (dynamic) environment. Results of such analysis confirm a strong influence of geography on the convergence process among EU regions. They also show that "intraregional" (i.e. within groups of neighbouring regions) is much stronger than "interregional" (i.e. between groups of neighbouring regions) convergence. This approach is beyond the scope of this paper but certainly opens very promising avenues for future research.

5. Conclusions

This paper has reviewed a number of methods and instruments developed for the analysis of economic and/or social inequalities and that can be used for examining disparities among EU regions. One objective of the paper was to produce an update analysis of the convergence process among EU regions in light of a panel of these instruments. Another was to show that instruments vary significantly in terms of their specificities and qualities and that it is therefore important to be aware of their limits when measuring the extent and evolution of regional disparities within the EU. A summary of the main properties of the convergence and inequality measures reviewed is included in the appendix.

More specifically, it has been stressed that while summary measures may be particularly convenient for synthesising complex information, they remain blind to a number of aspects that can be critical when it comes to assessing convergence among regions. The paper has thus extended the analysis of disparities among EU regions by relying on methods, such as Markov chain analysis, that allow for tracking individual movements within the distribution of regional GDP per head. This resulted in adding valuable information concerning the mechanisms at work in the convergence process. Most importantly, the examination of the distribution dynamics suggested that convergence among EU regions is stronger than that which is indicated by summary measures. In particular, it revealed that convergence is taking place even within groups of regions like the EU-15 for which such movement remained undetected by summary measures.

This calls for a prudent attitude when drawing conclusions based on this type of instrument. By summarising the dispersion of the distribution into one measure, they indeed provide convenient and helpful indicators. However, they fail to capture movements that may be relatively small in statistical terms but are nevertheless of importance from a policy point of view.

These results also underline that the analysis of convergence is in fact complex. Serious assessments of convergence cannot be based on a single measure but rather on a panel of instruments and a sound interpretation of their results, taking into account their complementarities. Finally, even if the analysis of regional disparities is conducted thoroughly, it says little about the effectiveness of EU Cohesion Policy. Keeping track of regional disparities and monitoring their evolution is definitely of key importance for the design and management of Cohesion Policy. However, it must be kept in mind that the analysis of disparities, whether pointing to the presence or absence of convergence, generally cannot be used to infer firm conclusions concerning the success or failure of the policy. For this, it is necessary to proceed to further analysis, notably by controlling other variables likely to affect the convergence process, as a proper econometric analysis would do. However, given the complexity of Cohesion Policy (e.g. the large diversity of the programmes implemented under Cohesion Policy) and its particular institutional context (e.g. the fact that it is designed and managed within a multi-level governance system), even this is probably insufficient. The rigorous assessment of its impact also requires evaluation at a more micro-economic level and the use of appropriate counterfactuals and control groups.

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Appendix – Main properties of inequality and convergence measures

	Measure	Visual / Quantitative	Range	Main characteristics
Beta-convergence	**Beta coefficient**	Q	0 - ∞	Estimated rather than computed
Sigma-convergence	**Coefficient of variation**	Q	0 – 1	Sensitive to changes in the mean, in particular when the mean value is near zero.
	Gini index	Q	0 – 1	Sensitive to changes in inequality around the median/mode.
	Atkinson index	Q	0 – 1	Weight given to gaps between incomes in lower or upper tail of the distribution parameterised through the "aversion to inequality".
	Theil index	Q	0 - ∞	Gives equal weights across the distribution. Does not have a straightforward interpretation.
	MLD	Q	0 - ∞	Gives more weight to gaps between incomes in the lower tail of the distribution. Does not have a straightforward interpretation.
Analysis of distribution	**Kernel estimation**	V	-	No possibility of statistical inference. No possibility of identifying individual regions.
	Cumulative frequency	V	-	No possibility of statistical inference. No possibility of identifying individual regions.
	Salter graphs	V	-	No possibility of statistical inference. Possibility of identifying individual regions.
	Markov chain analysis	Q	-*	Possibility of statistical inference and of identifying individual regions.

Moreover, there are five key axioms or properties that aggregate/summary inequality measures should ideally comply with:

1. *Mean or income scale independence* - The inequality measure is invariant to proportional increases or decreases in every region's GDP per head.
2. *Principle of Population* – The inequality measure is invariant to replications of the population.
3. *Symmetry or Anonymity* - The inequality measure is independent of any characteristic of regions other than the dimension under which disparities are measured (e.g. GDP per head).
4. *The Pigou-Dalton Transfer Principle* - The transfer of income from rich to poor reduces measured inequality.
5. *Decomposability* – The inequality measure may be broken down by population groups or income sources or in other dimensions.

All Sigma-convergence measures reviewed in this paper respect axioms 1 to 4. The Theil index and MLD satisfy all axioms.

Any question, comment or contribution should be sent to the following address: regio-papers@ec.europa.eu

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