ECOLOGICAL FALLACY IN A TIME SERIES CONTEXT: EVIDENCE FROM THE SPANISH REGIONAL UNEMPLOYMENT RATES*

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Abstract:

The ecological fallacy (EF) is a common problem regional scientists have to deal with when using aggregated data in their analyses. Although there is a wide number of studies considering different aspects of this problem, little attention has been paid to the potential negative effects of the EF in a time series context. Using Spanish regional unemployment data, this paper shows that EF effects are not only observed at the cross-section level, but also in a time series framework. The empirical evidence obtained shows that analytical regional configurations are the least susceptible to time effects relative to both normative and random regional configurations, while normative configurations are an improvement over random ones.

Keywords: ecological fallacy, time series, constrained clusters, Theil index, unemployment rates.

JEL Codes: O18, E24, C61.

1. Introduction

The ecological fallacy (EF) is a well-known error in statistical inference that occurs when conclusions for aggregated data do not reflect the reality of individuals belonging to this aggregation. This problem has also been referred to as aggregation bias in the literature. EF was first introduced by Robinson (1950) and studied by many other authors since that time, among them Richardson et al. (1987), Piantadosi et al. (1988), Greenland and Morganstern (1989), and Richardson (1992).

EF is a common problem regional scientists have to deal with because the units of study (regions) in most cases are derived from data aggregated from smaller units. The reasons to aggregate these basic spatial units into larger ones could be related to the necessity to create meaningful units for analysis (Yule and Kendall 1950), to preserve confidentiality, to minimize population differences, to reduce the effects of outliers or inaccuracies in the data, or, simply to facilitate the visualization and interpretation of information in maps (Wise et al. 1997, 2001).

Researchers have developed two approaches to minimize the effects of EF. The first approach, and perhaps the most studied, has been to formulate statistical models or estimation procedures to reduce the aggregation bias. Gotway and Young (2002) provide a complete overview of various statistical solutions related to this topic. The second approach, proposed by Openshaw (1977), formulates a geographical solution to this problem. It consists of reducing the aggregation bias by controlling the way small areas are aggregated into larger regions rather than performing sophisticated data transformations or parameterizations to control the aggregation effects.

This paper follows the second approach to study the power of spatial aggregation models to minimize the EF effects in a time series context. This temporal dimension has been omitted in the previous literature. Two types of spatial aggregations are considered in this paper: i) normative regions (officially predefined official aggregations such as counties, districts or states), and ii) analytical regions designed using three algorithms whose aggregation criteria include a temporal dimension.

Based on the idea that intraregional homogeneity is a way to minimize aggregation bias, it is expected that in studies involving time series analysis the spatial units (regional configuration) are consistent through time, i.e. for a given regional configuration the intraregional homogeneity remains as high and stable as possible. When such a consistency does not exist, a specific regional configuration could be meaningful in period t but it may become unsuitable in period $t+k$. When the regional configuration does not take into account the possible time variation, it may not be possible to determine whether the obtained results reflect the underlying nature of the considered phenomena or an improper spatial aggregation of data. In this case, statistical inference will be based on regions that are representing different realities depending on time. To our knowledge, the only work that has partially considered this issue is Norman et al. (2003) who suggest possible approaches to harmonize time series data collected from geographical units that have had boundary changes over time.

This paper uses data from unemployment rates in Spain to illustrate in a simple way the capacity of spatial aggregation models to minimize the EF effects in a time series context. Throughout the paper, it will be assumed that there is a necessity to aggregate data from smaller regional units into big ones in order to characterize the geographical distribution of unemployment and its evolution. In particular, provincial (NUTS III) time series of unemployment rates in Spain are used to assess intraregional homogeneity using the Theil's inequality index and its temporal stability when these provinces are aggregated into NUTS II and NUTS I regions.[1] These components are also analyzed in a large number of regional configurations in order to assess whether or not the use of analytical instead of normative regions could be useful for minimizing the EF effects.

The rest of the paper is organized as follows: Section 2 briefly describes the design of this research and some methodological issues. Section 3 presents the results of the analysis of regional homogeneity and temporal stability of normative and analytical regions. Finally section 4 summarizes the main conclusions of this study.

2. Research design and methodological issues

This section explains the motivation for analyzing the Spanish regional unemployment rates and describes the methodology applied in the next section of the paper.

2.1. Motivation for the analysis

There are three characteristics that make Spanish unemployment rates a good candidate for exploring the role of aggregation models in minimizing the aggregation bias in a time series context. They are regional disparities, spatial dependence and temporal dynamics. These three characteristics of unemployment rates will be briefly described for the quarterly time series data of the 47 Spanish provinces (NUTS III regions) between 1976 and 2003.

Regional disparities. Like many other economic variables, unemployment rates show important regional disparities that make their analysis unrepresentative at a nationwide level (Jimeno and Bentolila 1998; Alonso and Izquierdo 1999; López-Bazo et al. 2005). For the analyzed period, Spanish unemployment rates at the provincial level range from 0.12% (1976QIII) to 45.12% (1995QI), with a maximum variation range of 35.64% (1995QI). A better understanding of the magnitude of these disparities can be seen in Figure 1, which shows the variation coefficient of NUTS III unemployment rates during 1976-2003. This dispersion was considerably higher during the second half of the 70's.

These disparities make the study of aggregation effects of major interest to researchers because the more heterogeneous the areas the higher the possibility to have aggregation bias. This heterogeneity makes aggregating areas into homogeneous and spatially contiguous regions challenging.

Spatial dependence. Another characteristic of Spanish unemployment rates is the presence of positive spatial dependence at the NUTS III level (López-Bazo et al. 2002). The Moran's I statistic (Moran 1948) of first-order spatial autocorrelation was estimated.[2] The values for the standardized Moran's I, Z(I), are shown in Figure 2. All Z-values are greater than 2, indicating that the null hypothesis of a random distribution of the variable throughout the territory (non spatial autocorrelation) should be rejected.

Spatial dependence has two implications for this study. First, for spatial aggregation models, the presence of positive autocorrelation relaxes the requirement of contiguity constraint. If such positive dependence did not exist, spatial aggregation algorithms would not have a major advantage compared to other regional configurations generated at random. Second, for EF, the positive spatial autocorrelation provides a way to reduce the loss of information after the aggregation. The decrease in variance is moderated by the positive autocorrelation (Arbia 1986; Cressie 1993).

Time dynamics. Previous studies have reported important changes over time in the Spanish unemployment rates (Blanchard and Jimeno 1995; Marimon and Zilibotti 1998; López-Bazo et al. 2002) as well as significant differences among regions in terms of both cyclical sensitivity and persistence of regional unemployment (Bentolila and Jimeno 1995). To illustrate these changes, Figure 3 presents the average quarterly unemployment rates for two sub-periods, 1976-1990 and 1991-2003, which corresponds to the two long business cycles experienced by the Spanish economy in the last 40 years. Important differences are found in both sub-periods with average unemployment rates ranging from 4.2% to 25.6% for 1976-1990, and 6.9% to 34.4% for 1991-2003. A comparison between sub-periods shows a tendency toward higher values of unemployment rates. In fact, only five out of forty-seven Spanish provinces reduce the average unemployment rates with respect to the first sub-period.

These changes over time facilitate the evaluation of EF from a time dimension. These dynamics make it possible to evaluate the contribution of spatial aggregation algorithms to the reduction of EF over time. The challenge here is to design consistent regional configurations that keep intraregional homogeneity high and stable so that EF effects are reduced.

Summarizing, the need for aggregating areas into homogeneous regions is related to the presence of regional disparities; the contiguity constraint is related to the presence of a positive spatial autocorrelation; and changes over time stress the role of consistent regional configurations.

FIGURES 1, 2 and 3 ABOUT HERE

2.2. Spatial aggregation methods

This subsection briefly describes the spatial aggregation (regionalization) algorithms that will be used to design analytical regions. It is important to note that this subsection does not attempt to provide a survey of the different regionalization methods suggested in the literature nor to assess their relative performance. Literature reviews of regionalization methods have been done by Fischer (1980), Murtagh (1985), Gordon (1996, 1999) and Duque et al. (2006).

There are two common characteristics among the regionalization algorithms that will be used in this paper. First, they aggregate a given set of areas into a predefined number of spatially contiguous regions while optimizing some aggregation criteria. And second, the three methods included are *supervised*, since they all assume that there is a prior knowledge about the aggregation process, including: relevant variables for the aggregation, number of regions to be designed, the regional spatial contiguity constraint and the existence of aggregation criteria. Although more than one classification variable could be used, we preferred to take a univariate approach to keep it as simple as possible and focus on the potential time effects of the EF. The capability of dealing with both cross-sectional and time variation is one of the reasons to select the three following regionalization procedures: K-means two stages, ARISeL and RASS.

K-means two stages

K-means in two stages is probably the simplest regionalization method. It was proposed by Openshaw (1973) as a methodological approach for regionalizing large datasets. The first stage applies any conventional partitioning clustering algorithm, in this case the k-means algorithm (MacQueen 1967), to aggregate areas that are similar in terms of a set of variables. In the second stage, each cluster is revised in terms of spatial contiguity by applying the following rule: if the areas included in the same cluster are geographically disconnected, then each subset of contiguous areas assigned to the same cluster is defined as a different region.[3] Openshaw and Wymer (1995) formalized this method on a step-by-step basis for classifying and regionalizing census data.

Note that the number of clusters defined in the first stage is always less than or equal to the number of contiguous regions resulting in the second stage. Thus, adjustments in the number of clusters are required in order to obtain the desired number of regions which, in some cases, is not possible. For example, an increment (reduction) of one unit in the number of clusters in the first stage can generate an increment (reduction) greater than one in the number of regions in the second stage (Wise et al. 1997).

Openshaw and Wymer (1995) stressed that regional homogeneity is guaranteed in the first stage. Moreover, this strategy may also help in providing evidence of spatial dependence between the areas. Thus, when the clusters in the first stage tend to be spatially contiguous, it may imply that the classification variables have some spatial pattern.

However, as shown by MacQueen (1967), this algorithm only allows improving moves. This characteristic makes the algorithm to converge quickly in part because it can be easily trapped in suboptimal solutions. Finally, only improving moves make the algorithm very sensitive to changes in the initial centroids.

ARISeL (Automatic Regionalization with Initial Seed Location)

Duque and Church (2004) introduced the Automatic Regionalization with Initial Seed Location (ARISeL) algorithm where special attention is paid to the design of a good initial feasible solution before performing a local search by moving areas between regions. It is an extension of AZP-tabu, a well-known algorithm proposed by Openshaw and Rao (1995). The algorithm has two stages. The first stage uses a seeded regions strategy to generate an initial feasible solution.[4] Information about how the aggregation criterion changes through the assignation process is used to make changes in the initial set of seeds. This first stage generates a set of feasible solutions from which the best solution is chosen for further refinement in a second stage which proceeds by applying a local search process based on a tabu search algorithm (Glover 1977, 1989, 1990). Using a good feasible solution as an input to the second stage reduces both the possibility of getting trapped by a local optimal solution and the number of moves performed during the second stage.

RASS (Regionalization Algorithm with Selective Search)

Regionalization Algorithm with Selective Search (RASS) was developed by Duque (2004). Its main assumption is that the design of contiguous and homogeneous regions is relevant only if there are disparities between the areas which justify the design of more than one region, and some evidence of spatial dependence which justifies the requirement of spatial contiguity. If these two properties are present in the data set, then the available information about the relationships between areas can be crucial in directing the search process in a more selective, efficient and less random fashion. The algorithm starts by selecting a subset of m neighboring regions. The areas belonging to those regions are passed to an optimization model to re-aggregate them into m regions. Next, taking into account information about the relationships between the areas, the algorithm decides which region should leave the set of neighboring regions and which region should be added to the set in order to run the optimization model again. Thus, the set of regions passed to the optimization model keeps changing throughout the iteration process until a convergence criterion is satisfied.

The aim of RASS is to take advantage of the optimization model by applying it to a set of regions instead of trying to solve the whole problem at once. The local improvements achieved with the optimization model may be more difficult to obtain with an area-swapping scheme.

Table 1 describes the aggregation criteria (or objective function) used in each algorithm.[5] They all consist of a measure of intraregional heterogeneity that takes into account a time dimension. The aim of each algorithm is to minimize the objective function value in such a way that the intraregional heterogeneity over time is as low as possible. In the context of unemployment time series, this implies that neighboring areas (provinces) with similar unemployment rates during the period 1976-2003 will be likely to be assigned to the same region.

TABLE 1 ABOUT HERE

3. Empirical evidence

3.1. Normative and analytical regions

Figure 4 presents the analytical and normative aggregations at the two considered scales (15 and 6 regions), as well as their respective objective function value.[6] Note that analytical regions were designed in such a way that the regional configuration for six regions is nested inside the regional configuration of 15 regions. This nested structure is also a characteristic of the NUTS regions.

Three results can be derived from this figure: first, regional configurations using analytical techniques are quite different from the normative ones. Second, according to the objective function values, the internal heterogeneity (objective function value) is clearly lower for analytical regions than for normative ones. And third, analytical regions are closely related to the spatial distribution of unemployment rates presented in Figure 3. It is important to note that when applying the k-means algorithm it was impossible to design six regions. For k=3, five, instead of six, contiguous regions were generated, which was closes to the desired number of regions.

FIGURE 4 ABOUT HERE

3.2. Measuring intraregional heterogeneity: Theil's inequality index

As it was introduced in section 1, this paper relies on the assumption that intraregional homogeneity is a way to reduce the aggregation bias, or EF. In this subsection intraregional homogeneity will be described for both analytical and normative regions. The aim is to evaluate the capacity of these two types of aggregation methods to keep intraregional homogeneity as stable and high as possible over time.

Following a similar approach to the one applied in a different context by Batty and Sikdar (1982), intraregional homogeneity will be measured by applying the Theil's inequality index (Theil 1976).[7] Figure 5 shows the Theil index, total and decomposed, when average unemployment rates (1976-2003) of Spanish provinces (NUTS III) are aggregated into 15 and six regions. The most relevant result from Figure 5 is that the inequality within normative regions (upper left portion of the figure) represents a considerably high portion of total inequality. On the contrary, with analytical regions the portion of inequality within regions is clearly lower. When looking at the scale effects, all the aggregations show, as expected, an increment of intraregional inequality that seems to be more evident in normative regions where the inequality within regions is almost as high as the inequality between regions.

FIGURE 5 ABOUT HERE

In order to test the time effects of the EF, the Theil index was calculated for each quarter from 1976QIII to 2003QIII.[8] Results are shown in Figure 6. An important goal when normative regions (NUTS) were designed, more than 25 years ago, was that those regions should minimize the impact of the (inevitable) process of continuous change in regional structures. However, the obtained results show for both scales, NUTS II and NUTS I, an important variability of intraregional inequality over time (upper portion of Figure 6) that reflects important intraregional changes being inconveniently aggregated. Conversely, when designing analytical regions the time variation of the relative share of the within component is clearly low.

From Figure 6, it appears that the intraregional inequality component in normative regions and the level of global spatial autocorrelation (see Figure 2) are negatively correlated over time. The Pearson's correlation coefficient for the series is -0.84 at

NUTS II level, and -0.80 at NUTS I level. Both are significant at the 1% confidence level. For analytical regions this correlation is, on average, -0.55 at both scales.

FIGURE 6 ABOUT HERE

3.3. Statistical inference: analytical and normative regions versus randomly generated regions

Taking into account the previous results, an interesting aspect to analyze is whether the differences in the values of the Theil index components between normative and analytical regions are statistically significant. Three dimensions are covered: objective function value (aggregation criterion that measures the level of regional homogeneity), number of regions, and time effects. This analysis implies the consideration of inference in the context of regional inequality analysis.[9]

To begin with, Tables 2 and 3 summarize part of the results obtained in the previous subsection. In particular, they show that the relative share of the within component of the Theil index is directly related to the objective function value and inversely related to the number of regions.

TABLES 2 and 3 ABOUT HERE

In order to obtain an uncertainty measure for the Theil index components at different objective function values, 500 different regional configurations for 15 and six regions were pseudo-randomly generated taking as a starting point the 47 provinces (NUTS III).[10] It is worth mentioning that the simulations were done in such a way that each obtained regional configuration is feasible in terms of contiguity constraint. Moreover, special attention was paid to cover a wide range of possibilities in terms of internal homogeneity, but keeping in mind that extremely homogenous or extremely heterogeneous regional configurations will probably be less frequent. Figure 7 shows the histograms for the objective function values for the 500 simulated regional configurations at both scales.

Figure 8 shows the box plot diagram of the within component of Theil index for the 500 simulations for each scale. When considering six regions, the box plots show a lower dispersion range than the one obtained for 15 regions. This result reinforces the relevance of scale in the analysis of inequality, not only in the value of the within component, but also on its variability.

FIGURES 7 and 8 ABOUT HERE

At this point it is interesting to explore whether the observed differences in the within component of Theil index hold for different objective function values. Figure 9 shows the scatter plots of the objective function values versus the within component of Theil index. For each scale, the 500 points were divided into three groups according to the objective function value (*x*-axes). Figure 10 shows the box plots for the within component of Theil index for low, medium and high objective function values. As can be seen in both figures, dispersion in the values of the within component increases for higher values of the objective function, but the differences are not as high as expected.

These simulations were also used to build confidence intervals of the relative share of the within component of Theil index for the normative and the analytical regions. The results are shown in Table 4. From these results, it is possible to conclude that there are significant differences in the within component of the Theil index at the two different scales and also between normative regions and analytical regions.

FIGURES 9 and 10 ABOUT HERE

TABLE 4 ABOUT HERE

Finally the time variation of the within component of the Theil index for each regional configuration was checked to determine if it was different from the time variation obtained for the simulated regional configurations. With this aim, the standard deviation along time was calculated for the within component of the Theil index for each regional configuration (NUTS, K-Means, ARISeL and RASS) and the average value for the 500 simulated regional configurations. The results are shown in Table 5. In all cases the value of the standard deviation is lower than for the simulated regional configurations. It implies that both the normative and the analytical regionalization procedures are more consistent over time than random regional configurations. However, it is notable that analytical regions have lower standard deviation values, a result that was also discussed in subsection 3.2.

TABLE 5 ABOUT HERE

4. Conclusions

Using data for Spanish unemployment rates at the provincial level, the results obtained in this paper reaffirm the need for considering the potential effects of the ecological fallacy (EF) in a time series context.

Based on the assumption that intraregional homogeneity is a feasible way to minimize the negative effects of EF, this paper compares the differences in regional inequality when using officially established aggregations to the results obtained from designed analytical regions. Using the Theil index as a measure of inequality, regional homogeneity and scale effects have been evaluated in a time series framework.

The results showed that although both the normative and the analytical regional configurations are more consistent over time than random regional configurations, the analytical regions appear to be a more effective way to minimize the aggregation bias when the time dimension is considered.

Analytical regionalization algorithms that allow the inclusion of a time dimension within the aggregation criterion can be very useful in countries, like the United Kingdom, where administrative boundaries are subject to many changes that make the production of comparable statistics over time difficult (Norman et al. 2003). Although analytical regionalization techniques have been applied before (Openshaw 1984; Openshaw and Rao 1995; Commission of the European Communities et al. 1997; Martin et al. 2001), this paper reports on an aspect that has received little attention in the literature; the importance of including a time dimension that makes the resulting regions more consistent.

Further research will be conducted in two directions. First, simulation tools may be applied to evaluate the persistence of the results for datasets with different characteristics in terms of regional disparities, spatial dependence and time dynamics. And second, a deeper analysis of the space-time relationship between spatial dependence and regional consistency could contribute greatly to this field.

Notes:

[1] Nomenclature des Unites Territoriales Statistiques (NUTS) is the geographical system established by the Eurostat for the production of regional statistics within the European Union. According to Eurostat, "*normative regions are the expression of a political will; their limits are fixed according to the tasks allocated to the territorial communities, to the sizes of population necessary to carry out these tasks efficiently and economically, or according to historical, cultural and other factors*" (Eurostat, 2006).

[2] We discarded the use of the global Moran statistic due to the relatively low number of geographical units considered.

[3] Note the difference between cluster and region. A cluster does not satisfy spatial contiguity constraints, whereas a region does.

[4] The main characteristic of seeded regions is that each region is the result of selecting one area (seed area) to which other neighboring areas are assigned. This methodology was first proposed by Vickrey (1961) for solving districting problems.

[5] See Gordon (1999) for more information about other heterogeneity measures in classification models.

[6] The objective function values of k-means two stages have been expressed in terms of equation (2) in order to facilitate comparisons. The objective function values for NUTS aggregations are also expressed in terms of equation (2)

[7] See annex A for a description of the decomposition of the Theil index in the within and the between components.

[8] Data on unemployment rates for the different levels of aggregation are freely available on the Spanish *Instituto Nacional de Estadística*'s website: http://www.ine.es.

[9] To our knowledge, the only previous work that has considered this issue is Rey (2001).

[10] These simulations also take into account the nested configuration of both scales. Thus, every solution for 15 regions has its nested solution for 6 regions.

5. References

Alonso J, Izquierdo M (1999) Disparidades regionales en el empleo y el desempleo. *Papeles de Economía Española* 80: 79-99

Arbia G (1986) The modifiable areal unit problem and the spatial autocorrelation problem: towards a joint approach. *Metron* 44: 391-407

Batty M, Sikdar PK (1982) Spatial aggregation in gravity models. *Environment and Planning A* 14: 377-822

Bentolila S, Jimeno J (1995) Regional unemployment persistence: Spain 1976-1994. *C.E.P.R. Discussion Paper n.1259*

Blanchard O, Jimeno JF (1995) Structural unemployment: Spain versus Portugal. *American Economic Review* 85:212-218

Commission of the European Communities, Eurostat, Unit A4 GISCO (1997) *Geographical Information Systems in Statistics*. SUP.COM 95, Lot 115

Cressie N (1993) *Statistics for Spatial Data.* New York: Wiley

Duque JC (2004) *Design of homogeneous territorial units. A methodological proposal and applications*. PhD thesis, University of Barcelona. Spain

Duque JC, Church RL (2004) A new heuristic model for designing analytical regions. In: *North American Meeting of the International Regional Science Association, Seattle*

Duque JC, Ramos R, Suriñach J (2006) Supervised regionalization methods: A survey. mimeo

Eurostat (2006) Nomenclature of territorial units for statistics – NUTS. Statistical regions of Europe. http://europa.eu.int/comm/eurostat/ramon/nuts/home_regions_en.html (06/19/2006)

Fischer MM (1980) Regional taxonomy - a comparison of some hierarchic and non hierarchic strategies. *Regional Science and Urban Economics* 10: 503-537

Glover F (1977) Heuristic for integer programming using surrogate constraints. *Decision Science* 8: 156-166

Glover F (1989) Tabu search. Part I. *ORSA Journal on Computing* 1: 190-206

Glover F (1990) Tabu search. Part II. *ORSA Journal on Computing* 2: 4-32

Gordon AD (1996) A survey of constrained classification. *Computational Statistics & Data Analysis* 21: 17-29

Gordon AD (1999) *Classification*, 2nd ed. Boca Raton: Chapman & Hall-CRC

Gotway CA, Young LJ (2002) Combining incompatible spatial data. *Journal of the American Statistical Association* 97: 632-648

Greenland S, Morganstern H (1989) Ecological bias, confounding, and effect modification. *International Journal of Epidemiology* 18: 269-274

Jimeno JF, Bentolila S (1998) Regional unemployment persistence (Spain, 1976-94). *Labour Economics* 5:25-51

López-Bazo E, del Barrio T, Artís M (2002) The regional distribution of Spanish unemployment: a spatial analysis. *Papers in Regional Science* 81: 365-389

López-Bazo E, del Barrio T, Artís M (2005) Geographical distribution of unemployment in Spain. *Regional Studies* 3:305-318

MacQueen JB (1967) *Some methods for classification and analysis of multivariate observations*, Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, University of California Press 1: 281-297

Marimon R, Zilibotti F (1998) 'Actual' versus 'virtual' employment in Europe. Is Spain different?. *European EconomicReview* 42: 123-153

Martin D, Nolan A, Tranmer M (2001) The application of zone-design methodology in the 2001 UK census. *Environment and Planning A* 33: 1949-1962

Moran P (1948) The interpretation of statistical maps. *Journal of the Royal Statistical Society B* 10: 243-251

Murtagh F (1985) A survey of algorithms for contiguity-constrained clustering and related problems. *Computer Journal* 28:82-88

Norman P, Rees P, Boyle P (2003) Achieving data compatibility over space and time: creating consistent geographical zones. *International Journal of Population Geography* 9: 365-386

Openshaw S (1973) A regionalisation algorithm for large datasets. *Computer Applications* 3-4: 136-147

Openshaw S (1977) A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modeling. *Transactions of the Institute of British Geographers* 2:459-472

Openshaw S (1984) *The modifiable areal unit problem*. Concepts and Techniques in Modern Geography, 38 (GeoBooks, Norwich)

Openshaw S, Rao L (1995) Algorithms for reengineering 1991 census geography. *Environmentand Planning A* 27: 425-446

Openshaw S, Wymer C (1995) Classifying and regionalizing census data. In: Openshaw S (eds) *Census Users Handbook*. Cambridge, UK: Geo Information International, pp 239-270

Piantadosi S, Byar DP, Green SB (1988) The ecological fallacy. *American Journal of Epidemiology* 127:893-904

Rey S (2001) Spatial Analysis of Regional Income Inequality. *REAL Discussion Paper* 01-T9

Richardson S (1992) Statistical methods for geographical correlation studies. In: Elliot P, Cuzick J, English D, Stern R (eds) *Geographical and Environmental Epidemiology: Methods for Small Area Studies*. New York: Oxford University Press, pp 181-204

Richardson S, Stucker L, Hemon D (1987) Comparison of relative risks obtained in ecological and individual studies: some methodological considerations. *International Journal of Epidemiology* 16: 111-120

Robinson WS (1950) Ecological correlations and the behavior of individuals. *American Sociological Review* 15: 351–357

Theil H (1967) *Economics and Information Theory*. Chicago: Rand McNally and Company

Vickrey W (1961) On the prevention of gerrymandering. *Political Science Quarterly* 76: 105-110

Wise SM, Haining RP, Ma J (1997) Regionalization tools for exploratory spatial analysis of health data. In: Fisher MM, Getis A (eds) *Recent Developments in Spatial Analysis: Spatial statistics, behavioural modelling, and computational intelligence*. Springer, Berlin, pp 83-100

Wise SM, Haining RP, Ma J (2001) Providing spatial statistical data analysis functionality for the GIS user: the SAGE project. *International Journal of Geographical Information Science* 15: 239-254

Yule GU, Kendall MG (1950) *An introduction to the theory of statistics*, 14th ed. London: Griffin

FIGURES AND TABLES

Figure 1. Variation coefficient for the unemployment rate at NUTS III level

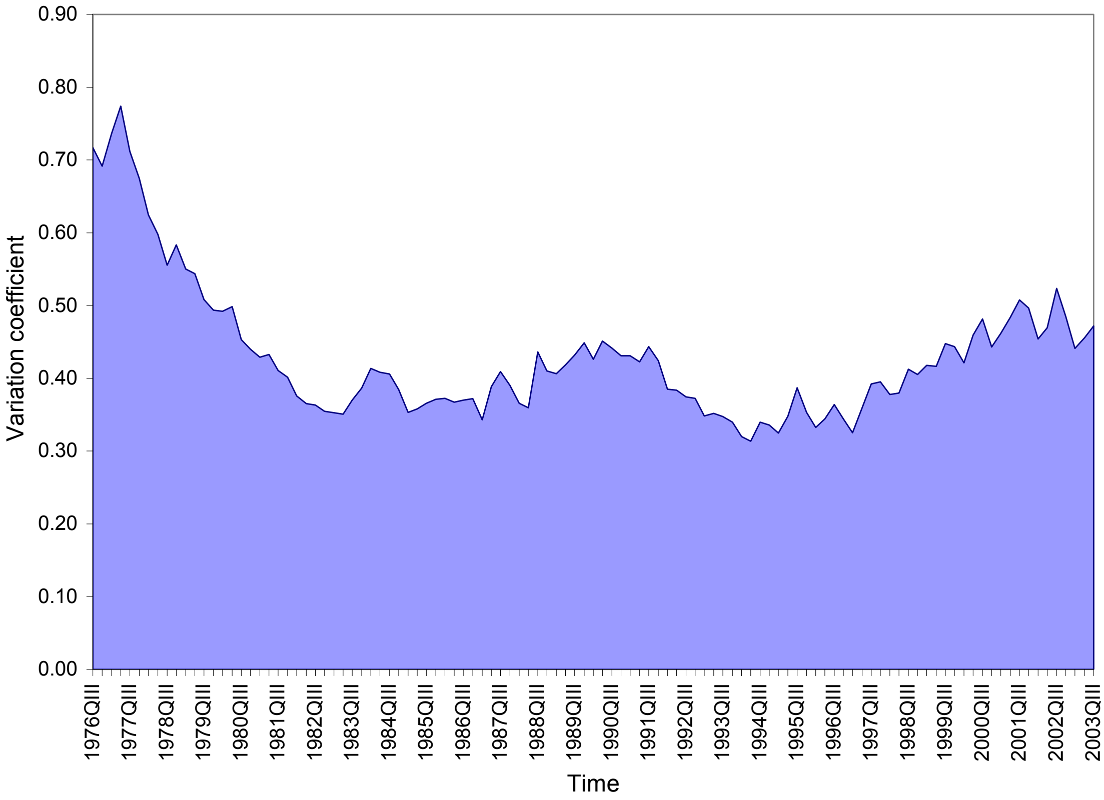


Figure 2. Z-Moran statistic for the unemployment rate at NUTS III level

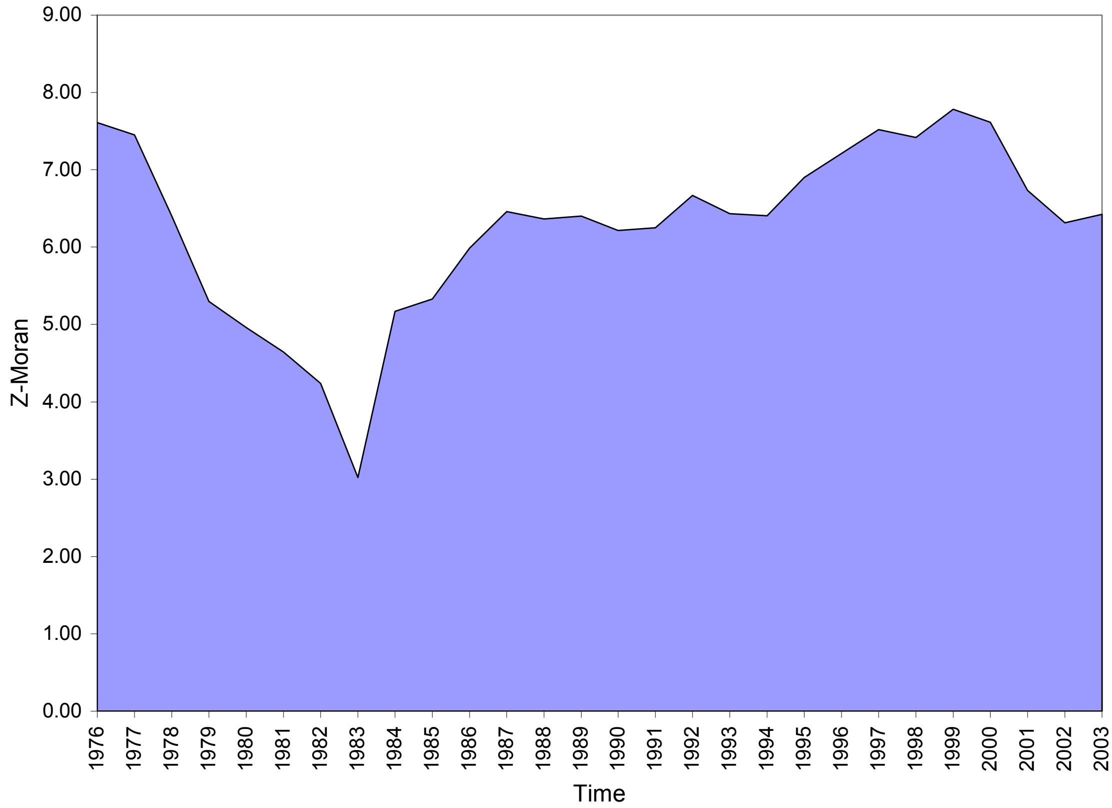
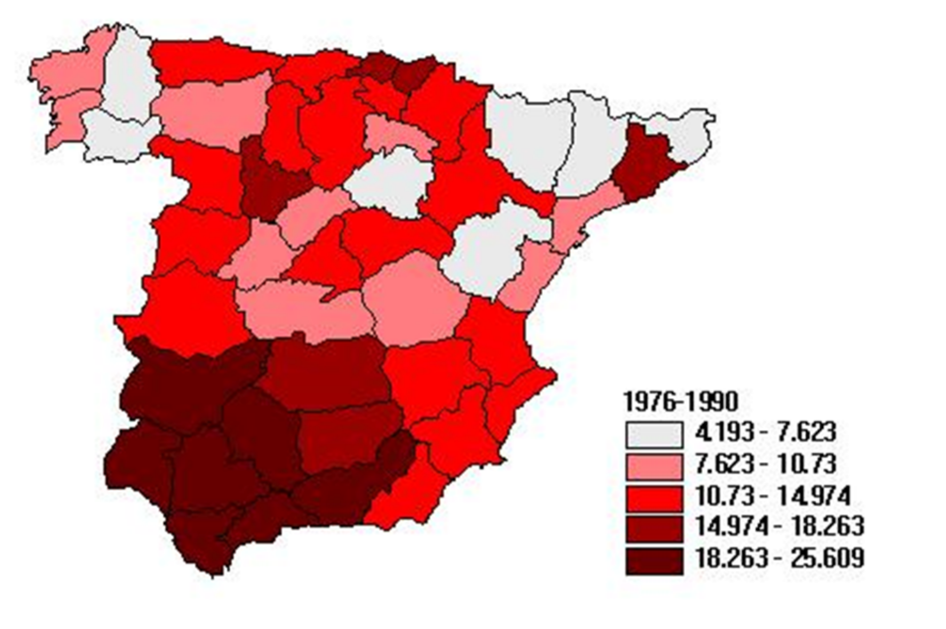


Figure 3. Average unemployment rates at NUTS III level

Average unemployment rate 1976-1990



Average unemployment rate 1991-2003

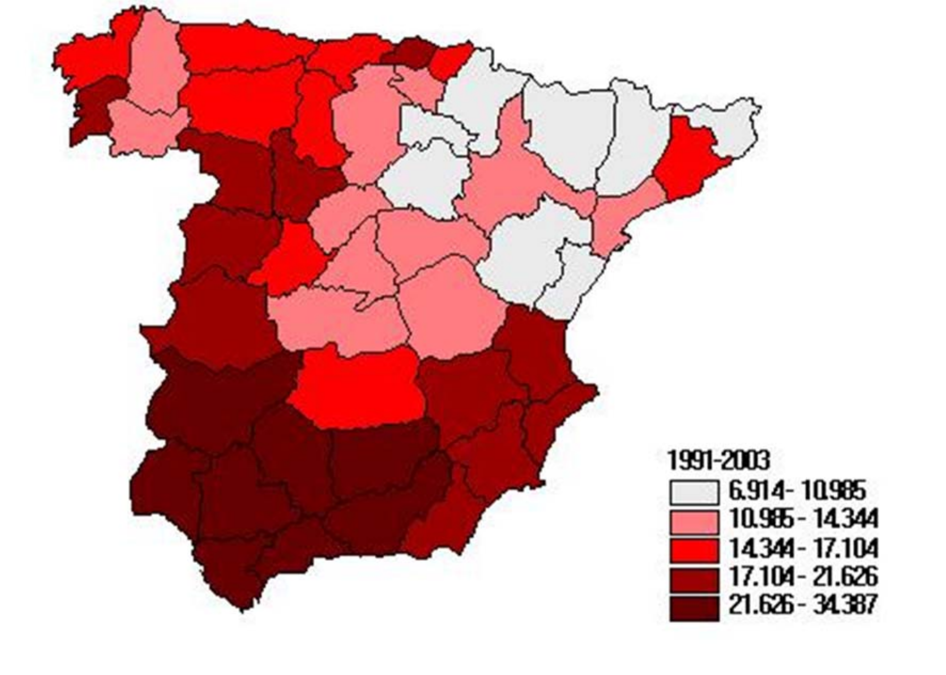


Figure 4. Regional configurations at scales 15 and 6

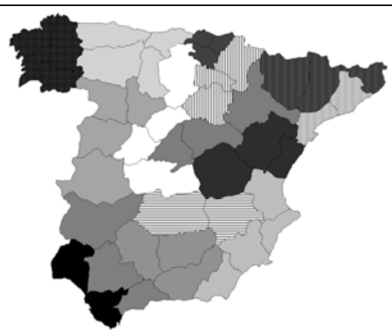
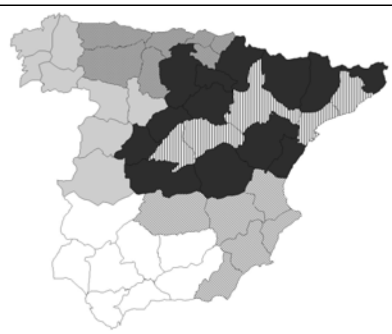
<table>
<tr><th>15 regions</th><th>6 regions</th></tr>
<tr><td colspan="2">NUTS</td></tr>
<tr><td>OF= 5636.28</td><td>OF= 14022.99</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">K-means two stages</td></tr>
<tr><td>OF= 3545.95</td><td>OF= 9750.08</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">RASS</td></tr>
<tr><td>OF= 1951.32</td><td>OF= 8059.27</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">ARISeL</td></tr>
<tr><td>OF= 1977.11</td><td>OF= 7931.91</td></tr>
<tr><td></td><td></td></tr>
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Figure 5. Theil index for the average unemployment rate 1976-2003 at scales 15 and 6

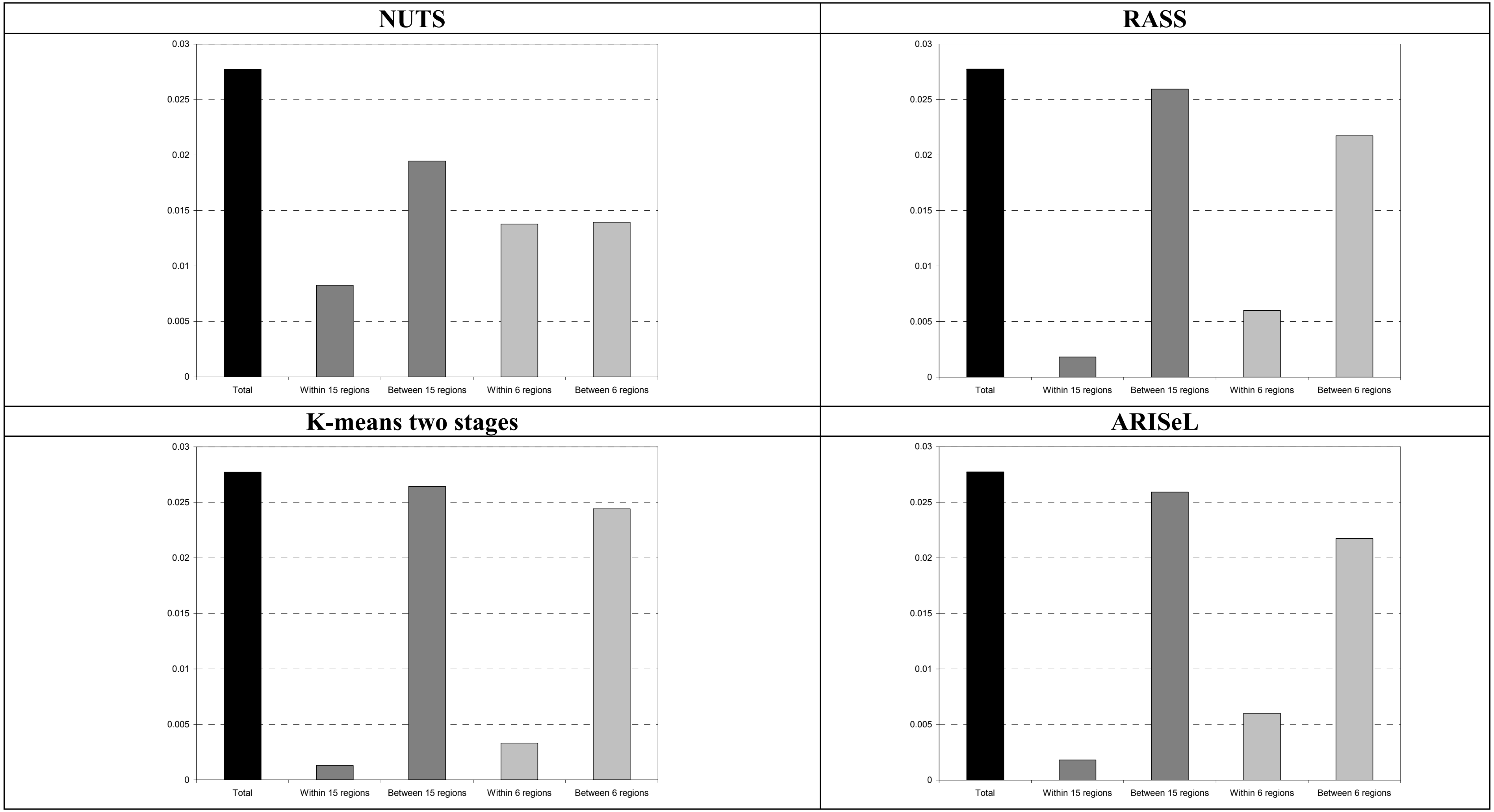
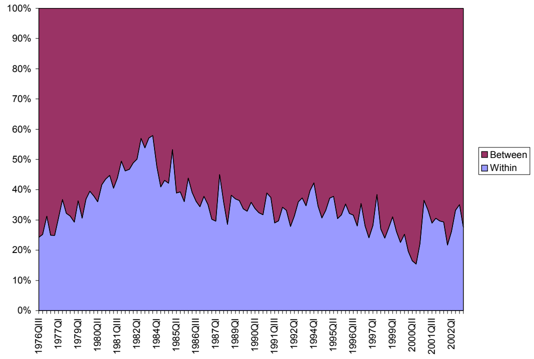
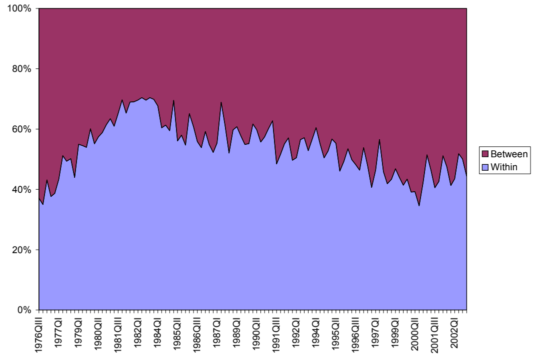


Figure 6. Theil index for the unemployment rate 1976-2003 at scales 15 and 6

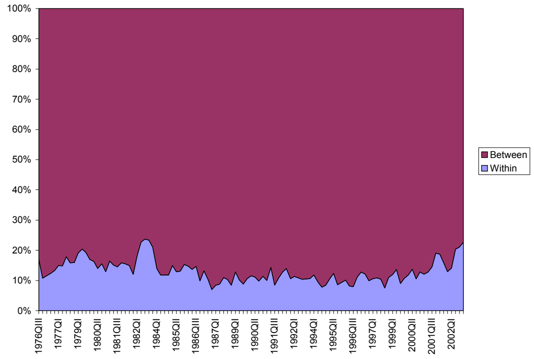
15 regions	6 regions

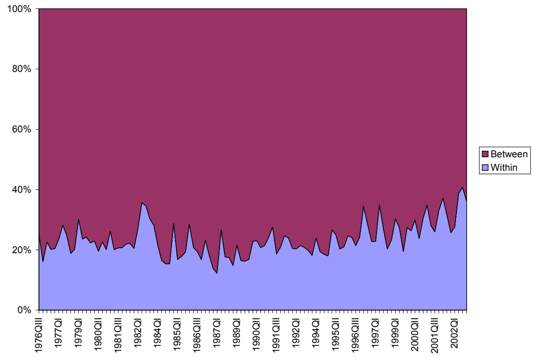
NUTS



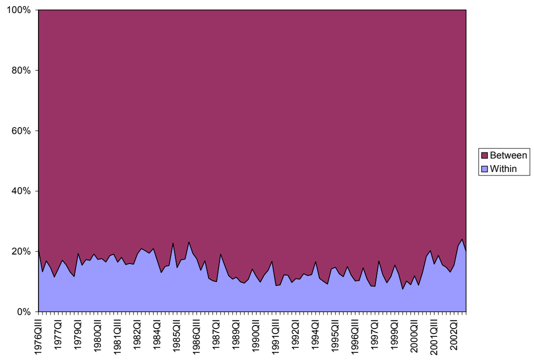


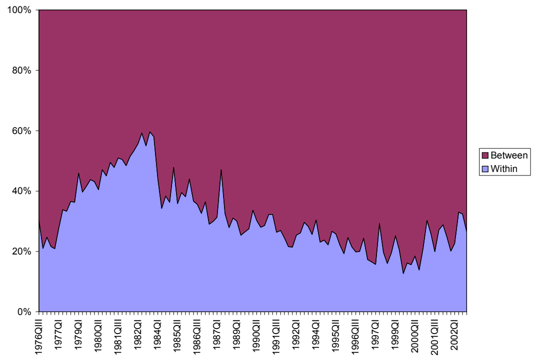
K-means two stages



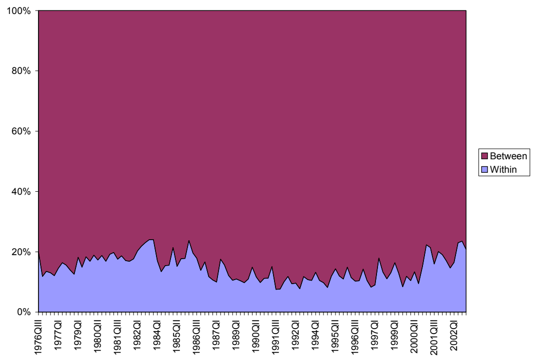


RASS





ARISeL



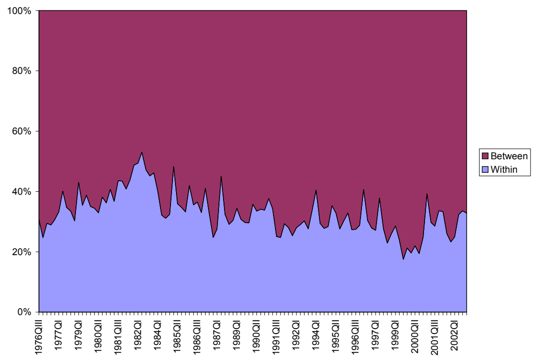


Figure 7. Histograms for the value of the objective function for the simulated regional configurations (15 regions, left; 6 regions, right)

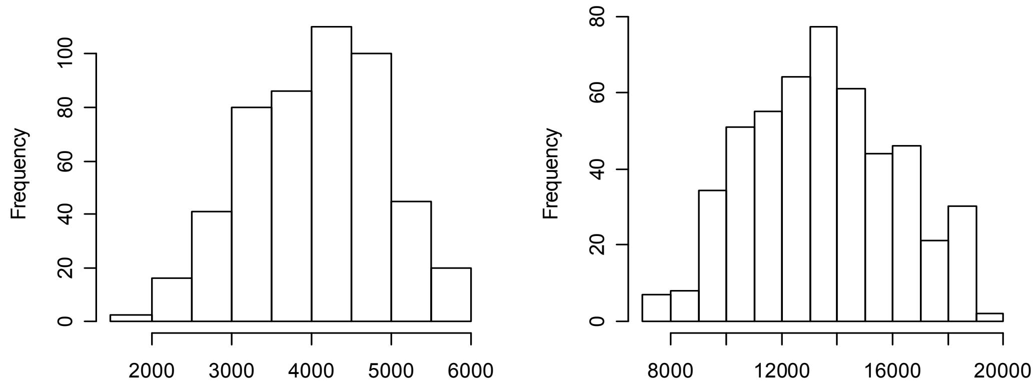


Figure 8. Box plot for the within component of Theil index for the simulated regional configurations (15 regions, left; 6 regions, right)

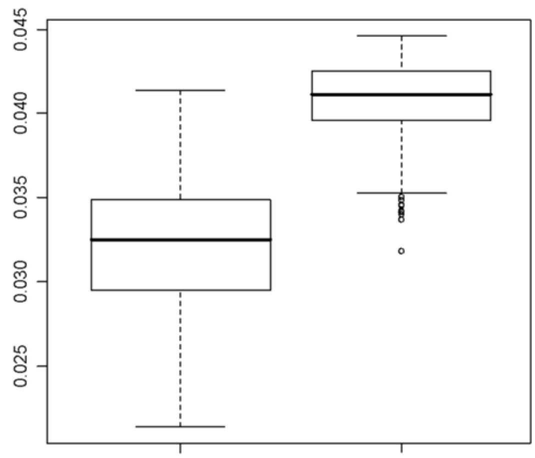


Figure 9. Scatter plot for the within component of Theil index and the values of the objective function for the simulated regional configurations
(15 regions, left; 6 regions, right)

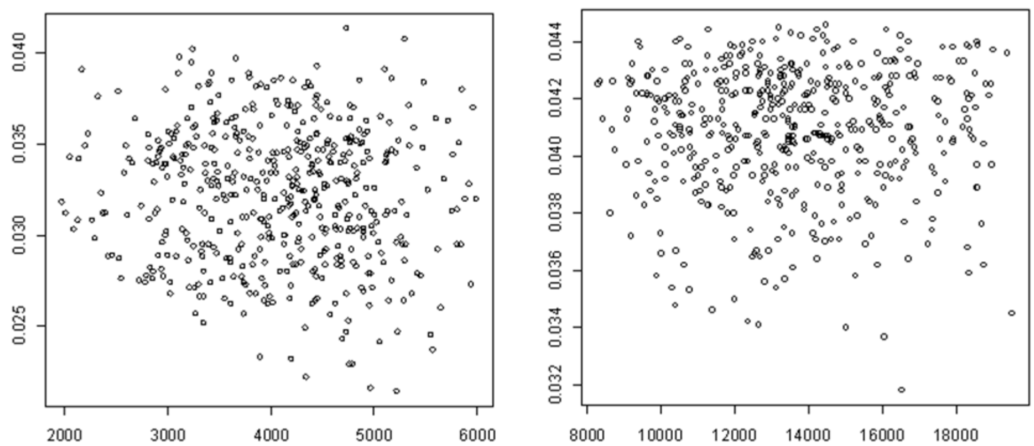


Figure 10. Box plot for the within component of Theil index for low, medium and high values of the objective function for the simulated regional configurations
(15 regions, left; 6 regions, right)

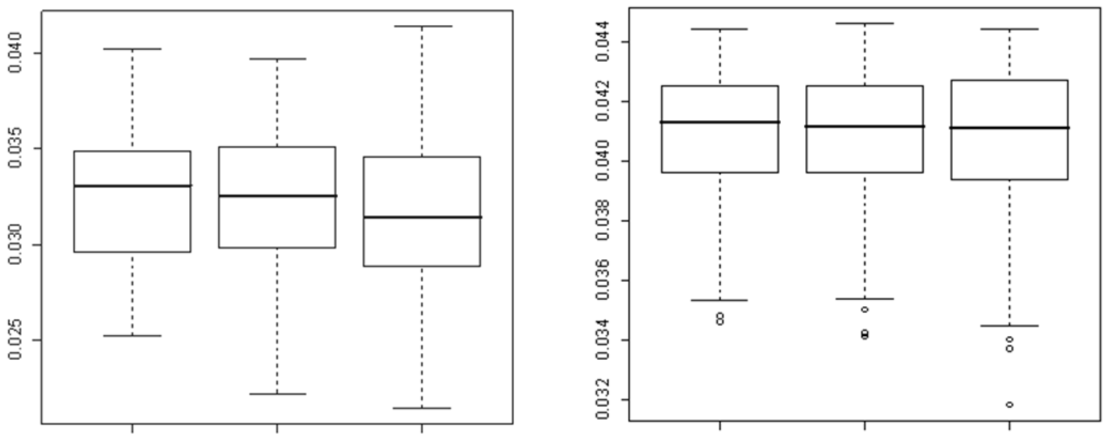


Table 1. Aggregation criteria used in each algorithm

	OF: *Minimize (Z)*	Parameters
K-means	$Z=\sum_{k=1}^{K}\sum_{i\in R_k}\sum_{t=1}^{T}\left(U_{it}-\mu_{kt}\right)^2$ (1)	$k=1,..,K$. Index of regions i. Index of areas R_k Set of areas in region k $t=1,\dots,T$. Index of time periods U_{it} Unemployment rate in area i in period t μ_{kt} Average Unemployment rate in region k in period t
ARISeL **RASS**	$Z=\sum_{k=1}^{P}\sum_{i,j\in R_k \mid i<j}\sqrt{\sum_{t=1}^{T}\left(U_{it}-U_{jt}\right)^2}$ (2)	$k=1,..,K$. Index of regions i and j. Index of areas R_k Set of areas in region k $t=1,\dots,T$. Index of time periods U_{it} Unemployment rate in area i in period t

Table 2. Summary results of the objective function value and the relevance of the within component when considering 15 regions

15 regions	Objective function	Relative share of the within component of the Theil index for average unemployment
NUTS II	5636.3	29.8%
K-MEANS	3545.9	4.7%
ARISEL	1977.1	6.9%
RASS	1951.3	6.5%

Table 3. Summary results of the objective function value and the relevance of the within component when considering 6 regions

6 regions	Objective function	Relative share of the within component of the Theil index for average unemployment
NUTS I	14022.9	49.7%
K-MEANS	9750.1	11.9%
ARISEL	7931.9	25.1%
RASS	8059.3	21.6%

Table 4. Confidence intervals for the relative share of the within component of the Theil index for average unemployment

	15 regions	6 regions
NUTS	19.0%-40.6%	38.4%-61.0%
K-MEANS	0%-15.5%	0.7%-23.2%
ARISEL	0%-17.7%	13.8%-36.4%
RASS	0%-17.4%	10.3%-32.9%

Confidence level: 5%

Table 5. Standard deviation along time of the within component of the Theil index

	15 regions	6 regions
Simulations*	0.012 (0.001)	0.016 (0.001)
NUTS I / II	0.005	0.007
K-MEANS	0.003	0.005
ARISEL	0.003	0.006
RASS	0.003	0.006

* Average value for the 500 regional configurations. In parenthesis, the standard deviation.

Annex A. The Theil index

The Theil index has been computed as follows:

$$T = \sum_{p=1}^{n} \frac{u_p}{U} \log \left[\frac{\left(\frac{u_p}{U} \right)}{\left(\frac{1}{n} \right)} \right]$$

where n is the number of provinces (47), u_p is the provincial unemployment rate indexed by p, and U represents the Spanish unemployment rate $U = \sum_{p=1}^{n} u_p$

Overall inequality can be completely and perfectly decomposed into a between-group component $T_g^{'}$, and a within-group component (T_g^W). Thus: $T = T_g^{'} + T_g^W$. With $T_g^{'} = \sum_{i=1}^{m} \frac{U_i}{U} \log \left[\frac{\frac{U_i}{U}}{\frac{n_i}{n}} \right]$ where i indexes regions, with n_i representing the number of provinces in group i, and U_i the unemployment rate in region i., and $T_g^W = \sum_{t=1}^{m} \frac{U_i}{U} \sum_{p=1}^{n_i} \frac{u_{ip}}{U_i} \log \left[\frac{\left(\frac{u_{ip}}{U_i} \right)}{\left(\frac{1}{n_i} \right)} \right]$,

where each provincial unemployment rate is indexed by two subscripts: i for the unique region to which the province belongs, and subscript p, where, in each region, p goes from 1 to n_i.