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**HEALTH INEQUALITIES IN THE EUROPEAN UNION:
AN EMPIRICAL ANALYSIS
OF THE DYNAMICS OF REGIONAL DIFFERENCES**

Laia Maynou

Marc Seaez

Jordi Bacaria

Guillem López-Casasnovas

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Health inequalities in the European Union: An empirical analysis of the dynamics of regional differences

Laia Maynou^{1,2,3}, Marc Saez^{1,2,4}, Jordi Bacaria^{5,3}, Guillem Lopez-Casasnovas^{6,4,7}

¹ Research Group on Statistics, Econometrics and Health (GRECS), University of Girona, Spain.

² CIBER of Epidemiology and Public Health (CIBERESP), Spain.

³ London School of Hygiene and Tropical Medicine, London, UK.

⁴ Center for Research in Health and Economics (CRES), Universitat Pompeu Fabra, Barcelona.

⁵ Instituto Tecnológico Autónomo de México (ITAM).

⁶ Department of Economics and Business. Universitat Pompeu Fabra, Spain.

⁷ Barcelona Graduate School (BSGE). Universitat Pompeu Fabra, Barcelona, Spain.

Corresponding author:

Prof. Marc Saez, PhD, CStat, CSci

Research Group on Statistics, Econometrics and Health (GRECS)

University of Girona

Campus de Montilivi, 17071 Girona

Tel 34-972-418338, Fax 34-972-418032 <http://www.udg.edu/grecs.htm>

e-mail: marc.saez@udg.edu

Abstract

In a panel setting, we analyse the speed of (beta) convergence of (cause-specific) mortality and life expectancy at birth in EU countries between 1995-2009. Our contribution is threefold. First, in contrast to earlier literature, we allow the convergence rate to vary and thereby uncover significant differences in the speed of convergence across time and regions. Second, we control for spatial correlations across regions. Third, we estimate convergence among regions, rather than countries, and thereby highlight noteworthy variations within a country. Although we find (beta) convergence on average, we also identify significant differences in the catching-up process both across time and regions. Moreover, we use the coefficient of variation to measure the dynamics of dispersion levels of mortality and life expectancy (sigma convergence) and, surprisingly, find no reduction on average in dispersion levels. Consequently, if the reduction of dispersion is the ultimate measure of convergence then, to the best of our knowledge, our study is the first that shows a lack of convergence in health across EU regions.

Key words: health convergence, beta-convergence, sigma-convergence, catching-up, spatio-temporal modelling, Bayesian models, INLA.

JEL: I14, I15, C33, C11

1.- Introduction

Numerous previous studies have analysed economic convergence, i.e. the reduction of disparities in GDP per capita and productivity, and its determinants (for a survey, see Durlauf *et al.* [1]). Economic convergence, however, can only give a partial picture of the dynamics of inequalities across countries [2]. Well-being is multifaceted and typically involves many aspects beyond income. Therefore, to analyse the reduction of disparities in well-being across countries, it would appear that simple income measures are insufficient. It is of course impossible to directly control for all the dimensions of life quality. However, it is possible to employ summary measures that encompass a wider range of factors of well-being [3,4]. In this paper, in an effort to look beyond income, we analyse convergence using life expectancy and (cause-specific) mortality in the EU-27 regions from 1995 to 2009.

Both life expectancy and mortality have been suggested as valid measures for the quality of life. Sen [4] and Maslow [5] argue, for instance, that one of our most basic needs is to prevent diseases and premature death. Furthermore, Becker *et al.* [6] propose longevity (i.e. life expectancy at birth) as not only a quantity but also a quality measure of well-being. Mayer [7] also proposes life expectancy as a suitable measure, arguing that it is the best indicator of population welfare available. Similarly, Sen [3] advocates mortality as an indicator of social ill-being. Mortality is directly and naturally related to many factors that determine quality of life. For instance, mortality can be taken as a summary measure of the availability of health care, social services and orderliness of urban living, among others.

From another point of view, there is abundant literature dealing with income-dependent health inequalities [8-18]. The literature indicates a causal relationship between health inequalities and income. However this causation can be bidirectional [19]. This topic has motivated the construction of different measures of health inequalities. In this sense, the Concentration Index measures the socioeconomic inequality of health taking into account both the level of health of each individual and as well as the rank of each individual in the socioeconomic domain [17]. This index, similar to the Gini coefficient used in our paper, is not without controversy related to, among others, the mirror property and the invariance to measurement scale [20-27].

Starting with Wennberg and Gittelsohn [28], there is also a large health economics literature on 'small area variations', analysing regional differences in health care

spending and outcomes¹. In fact, this connects with another brand of literature, more general from a macroeconomic point of view, on the concept of 'agglomeration'. One of the earliest and well-known theory is the Myrdal 'cumulative causation' [29]. According to this, one region will grow at the expense of another. Following Myrdal's agglomeration concept, Friedmann [30] attributes concentration to industrial and capital investment growth, Keeble et al [31] introduced the problem of accessibility and Krugman [32] with the 'New Economic Geography' aimed to explain the formation of economic agglomeration in certain geographical areas. These last theories have encouraged different applications of the concepts aiming to understand the variations among regions. For instance, a recent paper of Felder and Tauchman [33], uses these last concepts to determine the differences in the efficiency of health production in the German regions.

Convergence and Health

The concept of convergence, in its most general sense, is the reduction or equalising of disparities [34]. Convergence is a real and long-term phenomenon directly related to growth processes; that is, convergence exists when two or more countries' levels of wellbeing or development tend towards one another over time [35].

There are two well-known convergence hypotheses; the absolute and the conditional convergence hypothesis. In the former, the per capita income of countries or regions converges in the long term without taking into account initial conditions. Poorer countries and regions tend to grow faster than richer ones and there is a negative relationship between average growth rates and initial levels of income. It is assumed that all economies converge to the same stationary state [36].

On the other hand, the conditional convergence hypothesis assumes that the per capita income of countries and regions converge in the long term provided that their structural characteristics (i.e. technology, human capital, institutions, population growth rates, preferences) are the same [36,37]. With absolute convergence, the initial conditions are irrelevant. However, with conditional convergence, the equilibrium in each economy varies and each tends toward its own equilibrium.

Beta and sigma convergence

¹ Pointed out by one of the anonymous reviewers

The customary and most widely used instrument for measuring convergence is beta-convergence analysis. This began with the studies conducted by Baumol [38] and steadily grew in popularity [35, 36, 39, 40]. Beta-convergence is defined as the negative relationship between the initial level of income and the subsequent income growth.

Another instrument used to measure convergence, which became popular with the work of Quah [41], is sigma-convergence. This author showed that the traditional relationship in initial growth level did not give a clear answer for convergence, as it tended to be negative if differences in income were not reduced. According to his theory, there is sigma-convergence if the dispersion and inequalities between countries are reduced over time. Sigma-convergence can be calculated using different dispersion measures (variance, standard deviation or coefficient of variation).

Health convergence

Life expectancy and mortality, instead of GDP, have both been suggested as valid measures for the quality of life. In a cross-country study comprising of virtually the entire world, Preston [42] showed that while keeping income constant, the change in the longevity-income profile represented gains of fifteen years in life expectancy. In fact, macroeconomic studies of economic growth, such as Barro [43], have already found that life expectancy is a key predictor of economic growth. Pritchett and Summers [44] corroborated by using instrumental variables that countries with higher incomes enjoy greater health, suggesting, as did Anand and Ravallion [45], that the main reason for this relationship is the income levels of the poor in addition to public expenditure on healthcare. Wilson [46] studied the world distribution of life expectancy and found a decrease in its dispersion (i.e. sigma-convergence). Becker *et al.* [6], also in a worldwide study examining whether there is a positive correlation between longevity and income per capita, showed that convergence exists with longevity, while it does not with income. Gleit *et al.* [47] find that there is no sigma-convergence for life expectancy at older ages in high-income countries. Edwards [48] points out that there is beta-convergence but not sigma-convergence in life expectancy at birth across countries (although he finds sigma-convergence within countries). Clark [49], however, does not find beta-convergence, but rather that improvements in life expectancy have been greater for developing countries. Similarly, Eggleston and Fuchs [50], studying life expectancy in industrialised countries, point out that most gains in life expectancy have occurred in adult mortality, in particular for those over 65.

In terms of mortality, Edwards and Tuljapurkar [51] examining differences in the age pattern of mortality between countries over time (for practically the whole world), show that there is no sigma-convergence in mortality in industrialised countries. In the study previously referred to, Clark [49] finds that reductions in infant mortality are greater in high-income countries. Edwards [48] finds that reductions in infant mortality are greater in high income countries. If there is a positive correlation between initial income and mortality, then we could say that neither Edwards [48] and Clark [49] find (beta) convergence. Finally, d'Albis *et al.* [52] did not find (beta and sigma) convergence across countries when they considered the entire sample of industrialised countries, but they do provide some evidence of (sigma) convergence among a subset of countries.

Earlier literature does not give conclusive results for the use of these variables as measures of well-being. The main reason is that these variables have little variation in the short run. Significant changes are needed in social, health and demographic factors to provoke sufficient variation in mortality and life expectancy. However, in the long run, mortality and life expectancy variables can be more sensitive to changes than GDP [3].

EU-27 convergence

Our interest in the regions of the twenty-seven countries of the European Union (EU-27) lies specifically in one of the main priorities of the Treaty establishing the European Community: specifically economic and social cohesion. In keeping with Monfort [53], Article 158 of the Treaty (and its updated version Article 174) states, 'In particular, the Community shall aim at reducing the disparities between the levels of development of the various regions and the backwardness of the least favoured regions or islands, including rural areas.' Although it is true that the purpose of the cohesion policy goes far beyond mere economic convergence, the reduction of regional disparities has been measured as the convergence of regional levels of GDP per capita. In fact, pure economic convergence has become a major aspect in assessing the effectiveness of the European Cohesion Policy [53].

In respect of this, and adhering to Eckey and Türk [54], despite differences in model specification and observations, most studies on convergence in regional GDP per capita estimated (beta) convergence among EU countries, at both EU-15 and EU-27 level. However, the speed of convergence is not constant, neither in time nor between regions [53, 55]. With regards to sigma-convergence, Monfort [26] shows that convergence between EU-15 regions was strong up until the mid-90s and stabilised

thereafter (his analysis ends in 2005). However, as he found that disparities continued to decrease rapidly for the EU-27 regions, he concluded that the poorest regions in the new Member States were catching up with the Union's richer territories.

In summary, we formulate three hypotheses. Our first hypothesis is that by analysing regions instead of countries we can observe sufficient variability in the health variables of interest to estimate the (dis)similarity of their distribution over time. Since, at least at the aggregate level, there is much evidence of a positive association between income and health, our second hypothesis is that, when considering the time period at the end of the economic boom (i.e. 2005-2009), there will be beta-convergence in health between the EU-27 regions, but not sigma-convergence. Our third hypothesis is that, like economic convergence, the speed of health convergence is neither constant in time nor between regions.

Our contribution in this paper is threefold. First, we look beyond economic convergence and use life expectancy and mortality to capture a wider set of dimensions for the quality of life. Second, in contrast to earlier literature, we allow the convergence rate to vary and thereby uncover significant differences in the speed of convergence across time and space. Third, our dataset is more disaggregated because it comprises of regions rather than countries, and allows us to develop a more detailed picture of disparity dynamics.

The rest of the paper is organised as follows. We explain the methodology in section two. The results of the model are explained and discussed in section three. Finally, we conclude in section four.

2.- Methods

Data setting

We use data from 271 regions of the 27 EU member countries from 1995 to 2009. Data are obtained from EUROSTAT [56].

Our rationale for using regional data is twofold. First, it is the regions, rather than the countries, which are the subject of cohesion policies. Second, as we will explain below, with limited time series (T), as in our case (i.e., 1995-2009, 15 years), in order to obtain consistent estimates of the parameters of interest we needed a large N (thus instead of only seventeen countries, we have two hundred seventy-one regions).

Econometric model

Models are specified based on the well-known beta-convergence hypothesis [35-39], originally specified as a cross-section model:

$$g_T = \alpha + \beta y_0 + u \quad u \sim N(0, \sigma_u^2 I) \quad \{1\}$$

where g_T denotes the vector of (dependent variable) average growth rate in the period $(0, T)$; y_0 is the vector of (dependent variable) initial levels; u is a zero-mean and homoskedastic (σ_u^2 is the constant variance) normally distributed disturbance term; and α and β denote (unknown) parameters.

The absolute β -convergence hypothesis (equation {1}) rests on the assumption that there is a negative correlation between the initial level (of the dependent variable) and the growth rate (of such a variable). Therefore, β -convergence exists if the estimated value for β , the coefficient of interest, is (statistically significant) negative. If this is true, poorer economies (periphery) grow faster than richer ones (core) and will catch them up in the long run.

However, it is more reasonable to assume that a negative correlation exists between growth rate and, rather than level, the distance the level of the dependent variable is from its steady state equilibrium. Therefore, poorer regions do not necessarily grow faster than richer regions, because the latter may be even further from their steady state equilibria [57]. As a consequence, in this paper we use the conditional specification of the β -convergence hypothesis:

$$g_T = \alpha + \beta y_0 + X\gamma + u \quad u \sim N(0, \sigma_u^2 I) \quad \{2\}$$

where X is a matrix of explanatory variables (of convergence); and γ the associated (unknown) parameters.

In contrast to more standard studies, we do not specify cross-section, but rather spatio-temporal models, i.e. dynamic panel data, from a Bayesian approach. In fact, we want to explicitly consider the time dimension in our data. As we have argued, the convergence rate may have been different for each country and/or have varied during

the period under analysis. Furthermore, with small T, we need a large N in order to obtain consistent estimates.

In particular, we have specified the following model:

$$\begin{aligned} \log(y_{ijt}) = & \alpha_j + \beta_{jt} \log(y_{ijt-1}) + \gamma_{1jt} \log(gdppc_{jt}) + \gamma_2 \log(gdppc_{jt-1}) + \\ & \gamma_3 \log(gdppc_{jt-2}) + \gamma_4 \log(gdppc_{rate_{jt-1}}) + \gamma_5 \log(gdppc_{rate_{jt-2}}) + \gamma_{6jt} \log(Gini_{jt}) + \\ & \gamma_7 \log(sec_{ijt}) + \gamma_8 \log(univ_{ijt}) + \gamma_9 \log(pub_{exp_{jt}}) + \gamma_{10} \log(umy_{ijt}) + \gamma_{11} \log(ufy_{ijt}) + \\ & \gamma_{12} \log(bpg_{jt}) + S_i + u_{ijt} \end{aligned} \quad \{3\}$$

Where y denotes one of the four dependent variables we chose. First, as in most previous studies on health (in concurrence with the seminal paper of Sen [4]), we use life expectancy at birth (in years). However, instead of using total mortality, we prefer to use here (several) cause-specific mortality. Total mortality is actually a combination of many phenomena that could undermine this variable as an indicator of social ill-being [3]. In particular, we chose those causes of mortality most associated with socioeconomic deprivation in the literature [58-60]: ischemic heart disease mortality; cancer mortality; and larynx, trachea, bronchus and lung cancer mortality (cause-specific mortality was standardised as death rate per 100,000 inhabitants, 3-year average).

The subscript i denotes region ($i=1,...,271$); j country ($j=1,...,27$); t year ($t=1995, 1996,..., 2009$); α , β and γ denote unknown parameters; S denotes spatial random effects (see below); and u normally distributed disturbance term. Some data is missing for the four dependent variables mainly for the beginning of the period and specifically for some regions of Belgium, Denmark, Italy, Poland, Romania and Slovenia.

The main explanatory variables of the growth rate of the dependent variables are the GDP per capita ($gdppc$) (data available regionally), and the Gini index ($Gini$) (data available only at country level). We believe that the growth rate of the dependent variables is determined not only by the level of GDP per capita in absolute terms but also by its growth rate ($gdppcrate$). Note that we assume that the effects, if any, of GDP per capita (both in levels and as rates) on health convergence, are distributed in time. Hence, we include the current level (t) and two lags ($t-1$ and $t-2$) of GDP per capita and two lags ($t-1$ and $t-2$) of GDP per capita rate.

According to the EUROSTAT [56], the Gini index is defined as the relationship of cumulative shares of the population arranged according to the level of equivalised disposable income, to the cumulative share of the equivalised total disposable income received by them. More conveniently, it can be defined as twice the covariance between income and income ranks². The Gini coefficient ranges between 0 and 1, with 0 signifying complete income equality and 1 signifying complete inequality. In a meta-analysis of multilevel studies, involving a total of more than 61 million subjects, Kondo *et al.* [61] conclude that people living in regions with high income inequality (a higher Gini coefficient) have an increased risk of premature death, regardless of individual socioeconomic status, age, or gender. In particular, the mortality risk increases 8% per 0.05 increase in the Gini coefficient. Furthermore, these authors also seem to confirm a theoretical ‘threshold effect’ (a Gini coefficient equal to 0.3) above which disparities in health outcomes are observed.

Moreover, we also consider additional variables that may secondarily contribute to health convergence. These variables are available both at the regional and country level. The panel that we create with these data is unbalanced. Data was not available for all period and for all regions.

Regional level:

Umy: Youth male unemployment rate. Unemployment rate (15-24 years old) for young males from 1999 to 2009 in average for the regions of EU. For some regions, some data is missing for some years, mainly for the last period.

² We appreciate this definition from the other anonymous reviewers.

Ufy: Youth female unemployment rate Unemployment rate (15-24 years old) for young female from 1999 to 2009.

Sec: Percentage of secondary students Ratio of the sum of level 2 students (lower secondary or second stage of basic education), level 3 students (upper secondary education) and level 4 students (post-secondary non-tertiary education) over total population from 1999 to 2009. Some data is missing, mainly from Germany, Greece, Spain and United Kingdom regions.

Univ: Percentage of university students Ratio of the sum of level 5 and 6 students (tertiary education) over total population from 1999 to 2009. Data is missing also for the same countries as for the secondary students variables. These countries do not report to EUROSTAT all data on education.

Country level:

Bpg: External balance The ratio of exported goods minus imported goods over the country's GDP. All data available from 1995 to 2009, except for the first years of the period in Greece.

Pubexp: Public expenditure rate Ratio of goods and services bought by the State over the country's GDP. All data available from 1995 to 2009.

There are three reasons that led us to include these variables. First, since the main explanatory variable is the convergence of GDP per capita and given that in a previous study we found them to be associated with economic convergence in the EU (see details in Maynou *et al.* [28]), these additional variables might influence, at least, the initial situation prior to convergence. Second, some of these variables could be clearly associated with socioeconomic deprivation, e.g. unemployment and percentage of secondary and tertiary students [56]. Third, when estimating the models these variables are the ones giving us the best model in terms of goodness of fit (DIC criteria).

Some of the coefficients, and in particular the coefficient of interest, β , have subscripts. In fact, we specify (dynamic) random coefficient panel data models [62] or, in mixed models terminology, we allow (some of the) coefficients to be random effects [63]. In other words, we have allowed them to be different for the various levels we have considered. Thus, for example, the coefficient of interest, β , varies per year,

$$\beta_t = \beta + v_t$$

and also per country,

$$\beta_{jt} = \beta + v_{jt}$$

With respect to the other explanatory variables, the random effects are associated with different levels depending on the final model³.

When the random effects vary by country, we assume they are identical and independent Gaussian random variables with constant variance, i.e. $v_{jt} \sim N(0, \sigma_v^2)$.

When the random effects vary by year, we assume a random walk of order 1 (i.e. independent increments) for the Gaussian random effects vector (although we also assume a constant variance) [65].

$$\Delta v_{jt} = v_{jt} - v_{jt+1} \quad \Delta v_{jt} \sim N(0, \sigma_v^2)$$

We explicitly use a (dynamic) random coefficient specification because, when using a very complex design with multiple levels (regions, countries) and dimensions (spatial and temporal), there is an important heterogeneity both the initial conditions (ie intercept) in the coefficient of interest, as in the coefficients associated with the other explanatory variables. In fact, we are not only interested in control for this heterogeneity but also in model it, in particular as regards to the coefficient of interest.

³ We have a preliminary estimation of all models allowing variation on the three levels (country/time) for all coefficients. In the specification shown, we have provided only the best final models. Results not shown can be requested from the authors.

Spatio-temporal adjustment

In all models, the disturbance terms, although Gaussian, are not identically and independently distributed. In fact, with spatial data, as is in our case, it is necessary to distinguish between two sources of extra variability [66, 67]. First, the largest source is usually named ‘spatial dependence’, or clustering, and is a consequence of the correlation between the spatial unit and the neighbouring spatial units, generally the adjacent geographical areas. The closer areas are much more similar than the more distant ones. Part of this dependence is not really a structural dependence, but mainly due to variables (with a spatial behaviour too) that are not included in the analysis. The second source is independent, spatially uncorrelated extra variability, called uncorrelated or non-spatial heterogeneity, which is due to unobserved non-spatial variables that could influence the dependent variable [66, 67]. In our case, as we have the time dimension in our data, there is also temporal dependency (i.e. serial autocorrelation). Again, maybe not results of a dynamic behaviour of the dependent variable per se, but rather the omission of time-varying explanatory variables.

To take into account this spatio-temporal extra-variability, we introduce some structure into the model. Heterogeneity is captured by using the random effect associated with the intercept (α_j) (varying at a country level j). Temporal dependency is approximated through the random walk of order 1, and linked to the random effect associated with the parameter of interest, β_t (varying at a year level, t).

For spatial dependency, we follow the recent work of Lindgren *et al.* [68], and specify a Matérn structure [69]. In short, we use a representation of the Gaussian Markov Random Field (GMRF) explicitly constructed through stochastic partial differential equations (SPDE) which has as a solution a Gaussian Field (GF) with a Matérn covariance function [68]. To sum up, instead of using the Matérn in a regular lattice, which is the usual practice and would imply an estimation with a high computational cost as well as one that would be weak in terms of efficiency [68], we specify the structure of the spatial Matérn covariance in a triangulation (Delaunay triangulation – [70]) of the studied area with a low computational cost and, more importantly in our context, much greater efficiency.

Inference

As is well-known in random coefficient panel data models that unless the initial levels of the dependent variables are fixed constants [71], or the assumption of independence

between the regressors and the random effects is fulfilled, the estimates of the parameters will be inconsistent, even for sufficiently large T and N [62]. In dynamic panel data models, with the lagged dependent as the explanatory variable and, typically, with finite T , the assumption of independence does not hold [72-74]. However, Hsiao *et al.* [71] show that, even in this case, the use of a Bayesian approach performed fairly well. Under the Bayesian perspective, Zhang and Small [75], building on the Hsiao *et al.* estimator [71], allow the initial values to be correlated with the unit-specific coefficients and imposing stationarity on the unit-specific AR(1) coefficients. Their approach provides good estimates even when T is small. Maynou and Saez [76] show how the greater flexibility of the Bayesian estimation, a consequence of its hierarchical strategy, leads to better control of the biases associated to dynamic panel data models. This control allows us to obtain estimates of the parameter of interest with less bias and greater efficiency than other estimators commonly used in dynamic panel data models (in particular, GMM estimates).

Here inferences are performed using a Bayesian framework. This approach (~~more or less pure~~) is considered the most suitable for accounting model uncertainty, both in the parameters and in the specification of the models, either in cross-sectional studies [77-79] or in panel data models [71, 62, 80, 81]. Furthermore, only under the Bayesian approach is possible to model both spatial (heterogeneity and spatial dependence) and temporal extra variability, with relatively sparse data in some cases (see Table 1). Finally, within the Bayesian approach, it is easy to specify a hierarchical structure on the (observable) data and (unobservable) parameters, all considered random quantities.

Moreover, in this paper we prefer to relax the assumption of strict exogeneity, allowing a weak exogeneity of the lagged dependent variable, that is to say, that current shocks only affect future values of the dependent variable [80]. By doing this, we are able to obtain consistent estimates of the parameters of interest (even with fixed T). It is important to point out that this relaxation involves two requirements; first, a large N ; i.e. obtained in our case by considering regional data; second, identically and independently distributed error terms. This can only be achieved by the space-time adjustment explained above, imposing a certain structure on the original disturbance term.

Within the (pure) Bayesian framework, we follow the Integrated Nested Laplace Approximation (INLA) approach [82] (see [83] for further details).

All analyses are made with the free software R (version 2.15.3) [84], though the INLA library [65, 82].

3.- Results and discussion

Descriptive

In Tables 1 to 7 we provide some descriptive data. Table 1 collects the descriptive data for life expectancy at birth and Figure 1 show the evolution of life expectancy over time and across regions. We find heterogeneity between EU countries, in terms of life expectancy during the last fifteen years, ranging from Latvia (mean: 71.413) to Italy (mean: 80.317). However, the trend of this variable in all countries has been a gradual increase. The countries with higher life expectancy over the past fifteen years were Italy, Sweden and Spain, while Latvia, Lithuania and Estonia had the lowest life expectancy of the EU. Changes in life expectancy are seen in the long run. Although we only analyse fifteen years, we can see that regions are moving towards the upper levels of life expectancy.

Descriptive data for mortality due to ischemic heart disease are presented in Table 2 and in Figure 2. The trend for this variable in EU countries over the last fifteen years has been a gradual reduction. However, this rate has not been homogenous among the twenty-seven EU countries. Lithuania, Latvia and Estonia have had the highest rates of ischemic heart disease mortality, while France, Spain and Portugal have had the lowest. The map in Figure 2 shows that fewer and fewer regions suffer ischemic heart disease mortality. Eastern European countries are those with the higher rates, although these were falling.

In Table 3 and Figure 3, we have collected the descriptive data for cancer mortality. The common EU trend has been a gradual decrease, even if the map shows that this reduction has been mainly in the centre and south, but not in the east. The countries with higher rates of cancer death were Hungary, the Czech Republic and Poland, while, Cyprus, Finland and Sweden had the lowest rates in the period studied, 1995 to 2009.

The descriptive data for mortality due to lung cancer are collected in Table 4 and Figure 4. For this standardised death rate, there was no common trend among the EU countries from 1995 to 2009. The EU countries with higher lung cancer death rates were Malta, Hungary and Poland, and those with lower rates were Lithuania, Sweden and Finland. In Figure 4, we observe that mainly for the centre of Europe rates of lung cancer mortality have generally stayed the same or have increased.

Table 5 shows GDP per capita in the EU from 1995 to 2009. During the period studied, there was a common growth in GDP per capita among all EU countries. Luxembourg had the highest GDPPC, followed by Austria and Italy. Bulgaria had the lowest GDPPC, behind Portugal and Latvia. The map in Figure 5 does not show any sizeable changes in the EU regions in terms of GDPPC. However, while until 2005 some levels rose, after that date some central regions experienced a drop in their GDPPC.

Table 6 and Figure 6 collect descriptive data for the Gini Index. During the past fifteen years, inequalities have increased or decreased in EU countries, with no common path. Portugal, Latvia and Estonia were the countries with higher inequalities, while Slovenia, Sweden and Denmark were more equal (Table 6). The map shows us the representation of the Gini Index for the EU regions. The regions with more inequalities were in the east, while for the southern and central regions there has been a reduction in inequalities in last fifteen years.

Finally, in Table 7 we show the descriptive for the rest of explanatory variables, without distinguishing between countries or time period.

Results of estimating health convergence models

The results of estimating the models are shown in Tables 8. As stated above, the coefficient of interest in this analysis was β , which shows whether convergence or divergence existed between countries. However, we are not only interested in the existence of convergence; we also want to see the rate/speed of convergence/divergence. For this reason, we use the formula proposed by Šlander and Ogorevc [85] to compute the average speed of convergence⁴.

In Table 8.1, we show the results of the estimations for the four models. For the variable corresponding to life expectancy, we found significant convergence between EU countries, as the coefficient was negative, -0.819%, (that is to say, a convergence rate equal to 0.819%) and statistically significant (the 95% credible interval did not contain the zero). The only explanatory variable which had a (statistically) significant effect on the convergence of life expectancy was external balance (0.0001%). For mortality due to ischemic heart disease, we also found convergence between EU countries, as the coefficient of interest was negative, -1.557%, and statistically

⁴ $\frac{-\ln(1-\beta)}{T} * 100$

significant. In this model the significant explanatory variables which have an effect on convergence were GDP rates, 0.1214% (lag 1) and 0.12% (lag 2), and public expenditure, -0.0045%. As for standardised cancer rates, the model also showed convergence, -1.934%. In this case, the explanatory variables which had an effect on the convergence of cancer mortality were secondary students, -0.00183%, university students, 0.00075%, and young unemployed male, -0.00047%. For lung cancer mortality, we also found significant convergence among EU countries, -0.744%. The explanatory variables which had an effect on the convergence of lung cancer mortality were GDPPC, -0.00429% (lag 1), secondary students, -0.00269%, university students, 0.00142% young unemployed female, -0.00051%, and external balance, 0.00205%.

Summing up, our results indicate that there was (statistically) significant beta-convergence in life expectancy and mortality (ischemic heart disease, lung cancer and cancer) among the EU-27 regions for the studied period. In particular, the speed of the beta-convergence was, on average -1.934% per year (cancer mortality); -1.557% per year (mortality for ischemic heart disease); -0.819% per year (life expectancy); and -0.819% (mortality for lung cancer).

This means that, in terms of health, there was a catching-up process between the EU-27 regions between 1995 and 2009. Given the association (in the aggregate) between income and health variables, it might be reasonable to suppose that this catching-up process reflected the same process followed by economic convergence. The lower rate in beta-convergence in most of the health variables analysed for 2008 and 2009, two years after the start of the economic crisis, might exemplify this.

Table 8.2 shows the results of estimating the random effects. Note that the coefficients of some variables that were not statistically significant as fixed effects were estimated as statistically significant when considering them random effects. This was the case with the Gini coefficient. Our interpretation, therefore, is that although the Gini coefficient had no effect on convergence in health on average, it did have an effect on health convergence for some countries and in some of the years. Note also that this effect was very heterogeneous.

Although there was average beta-convergence for the regions of the EU-27 in the four health variables considered (i.e., the coefficient of interest, β , was negative and statistically significant), there were discontinuities in both convergence and the speed of this convergence between countries and over time. While there was no divergence

in any country, the rate of convergence in life expectancy at birth was less than average in Malta and higher in Portugal and the UK (in that order). As regards to mortality from ischemic heart disease, note that in Estonia, Luxembourg, Romania and Malta (in descending order) there was no convergence (because the coefficient associated, which was the sum of both the fixed and random effect for that country, was positive). Moreover, even with convergence (because in this case, the sum of both the fixed and random effect for that country, was still negative), it was not as fast as the average for the Netherlands but faster than Finland, Bulgaria and Greece. With regard to cancer mortality, France, Romania, and Ireland and, to a much lesser extent, Spain showed divergence. Moreover, the convergence rate was somewhat lower than average in the UK and higher in Greece, Finland, Portugal and Italy. Finally, with regard to mortality from lung cancer, we estimate a very slight divergence in Poland, Hungary and Austria. Among the converged countries, France and the United Kingdom converged at a slower rate and Greece at a much faster than average speed.

As regards to discontinuities in time, we estimated divergence only in cancer mortality for the year 2009. There were, however, differences in the rate of convergence for all variables. We estimated an above average rate for mortality from cancer (year 2008) and only slightly higher for lung cancer mortality (year 1999) and life expectancy (2003). Mortality from ischemic heart disease (2009) and lung cancer (2008 and 2009) were below average.

That is to say, although we find (beta) convergence on average, we also identify significant differences in the catching-up process both across time and regions. This spatio-temporal heterogeneity is not only different from those found for the European regions in economic convergence analysis (Eckey and Türk [54]. for EU-15 and EU-27; Monfort [53] for EU-27; Maynou *et al.* [55], for the Eurozone) but also from the health convergence analysis between countries [52], suggesting that beta-convergence in health may be the result of different phenomena than those affecting economic convergence. In this respect, for instance, following their entry into the EU in 2004, eastern European countries benefited from the EU cohesion policies that had boosted economic convergence; although in view of the results it is not clear that these policies also promote health convergence, at any rate for all of these countries and for all of the health variables. This can perhaps be attributed to the fact that prior to 2004 the health system in these countries had already reached quite high standards.

In order to analyse sigma convergence, we used the coefficient of variation for each health variable (Figure 7). It is important to note, however, that instead of using the

coefficient of variation calculated on the original variables, we used the calculated on the fitted values from the model {3}⁵. Note that sigma convergence did not occur in all cases. Only in life expectancy and lung cancer mortality were disparities reduced among the regions of the EU-27 for 1995-2009. However, the greatest reductions in disparities in life expectancy at birth occurred between 1995 and 2003, before increasing and then remaining stable from 2005 onwards. In the case of lung cancer mortality, disparities were reduced in 1999, before increasing until 2008 and then falling in the final year considered.

Using the coefficient of variation as a summary measure of sigma-convergence, we were unable to estimate a reduction in disparities between EU-27 regions over the fifteen years. As Sala-i-Martin [36] states, beta convergence is a necessary but not a sufficient condition for sigma convergence. But also, beta and sigma convergence do not always show up together because they capture different aspects [36]. Sigma convergence analyses whether the cross-country distribution of the (health, in our case) variable shrinks over time or not, while beta convergence relates to mobility within the given variable distribution. Therefore, we have estimated mobility within the distribution but the distribution itself has remained unchanged. In summary, if, as Quah [41] and other authors suggest, the concept of sigma-convergence is that which best reveals the reality of convergence, we cannot conclude that there was convergence in health among the regions of the EU-27 between 1995 and 2009.

Although we allowed the parameters, and in particular those of interest, to vary regionally, we were only able to estimate heterogeneity at a country-level. In a previous work on economic convergence between European regions, albeit in a smaller geographic area (the Eurozone), we were not able to estimate a spatial heterogeneity at the regional level either [55]. We believe that this is a consequence of how European policies are implemented, which, even if they have a regional dimension, are operational on a country level.

The effect of unequal income distribution, measured by means of the Gini index, on health convergence was very heterogeneous both between countries and between years.

⁵ That is to say, $CV = E(y_{ijt}) / (Var(y_{ijt}))^{\frac{1}{2}}$, both estimated in model {3}. Also note that this calculation can only be done easily following the Bayesian approach, where it is easier to make inferences about functions of parameters and/or predictions, in particular when the function is non-linear, as in our case (i.e. the dependent variables in {3} were non-linear functions of the health variables).

Discussion

The work could have several limitations. Let us discuss that in the same hierarchy used in the estimation of our models. First, we might have chosen other variables that would have explained the growth rate of the health dependent variables. We considered this possibility, but they could not be included due to a lack of data. In this respect, data for some variables are available at country level up to a maximum of three years, such as the abortion rate in the case of life expectancy, lifestyle as a percentage of smokers or drinkers, or the prevalence of obesity in cause-specific mortality. Other variables, such as immigrants from developing countries, are available at a country level for very few countries throughout the entire period considered in our paper (1995-2009). We preferred to include the Gini index as a proxy for income inequality and not include other variables such as poverty and social exclusion because of a lack of conclusive evidence regarding these variables, at least compared to the high position in the hierarchy of evidence provided by the study of Kondo *et al.* [61].

Second, the consistency of the estimates is totally dependent on the fulfilment of the hypothesis of weak exogeneity. This, in turn, depends on, at least one of their requirements. Once we made the spatio-temporal adjustment, the error terms should be identically and independently distributed. In this sense, we checked the absence of autocorrelation, or spatial or temporal, in the standardized residuals of all three models. In addition, using cross-correlation functions, we also checked the absence of (contemporary) correlation between the error terms and each of the regressors, including lagged dependent variables in particular.

Third, as in any Bayesian analysis, the choice of the prior may have a considerable impact on the results. In the second stage of the hierarchy we used, we allowed variation on the different levels for all coefficients, i.e. we allowed all the coefficients to be random effects. Then, we tested that the variance of the effects was equal to zero, i.e. the effects were actually fixed. Only when we rejected this null hypothesis, did we maintain the coefficient as a random effect. Furthermore, as regards to the third stage in the hierarchy, by increasing the precision (lowering the variance) we performed sensitivity analyses to assess how the prior on the hyperparameters influences the estimation. We found no significant differences.

An alternative structure for the spatial dependence would be the non-parametric approximation, conditional autoregressive model, CAR, either in its intrinsic [86] (the between-area covariance matrix is not positive definite) or proper [87] (matrix positive

definite) versions. To use this approach, areas (regions in our case) are taken to be neighbours if they share a common boundary. This approach provides good results if all regions are of a similar size and are arranged in a regular pattern, but results are not promising in other sets of circumstances [88]. In fact, as Simpson *et al.* [89] point out, CAR relies heavily on the regularity of the lattice and it is quite difficult to construct a CAR on an irregular lattice that is resolution consistent [90]. This is the main reason we chose to follow the SPDE approach in our work. As we mentioned earlier, instead of relying on a regular lattice, we specified the structure of the spatial Matérn covariance in a triangulation of the studied area, implying a low computational cost and much greater efficiency.

4.- Conclusions

Our main objective was to analyse the speed of convergence (beta) of (cause-specific) mortality and life expectancy at birth in EU regions between 1995-2009. Our results show that, in terms of health, there has been a catching-up process among the EU regions. Although we found (beta) convergence on average, we also identified significant differences in the catching-up process both across time and regions. This last finding differs from other studies done for the EU regions. Moreover, by using the coefficient of variation to measure the dynamics of dispersion levels of mortality and life expectancy (sigma convergence), we, surprisingly, find no reduction on average in dispersion levels. Consequently, if the reduction of dispersion is the ultimate measure of convergence, as various authors have agreed (e.g. Quah, [15]), then our study shows a lack of convergence of health across EU regions.

Conflicts of Interest

There are no conflicts of interest for any of the authors. All authors freely disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organisations within three years of beginning the submitted work that could inappropriately influence, or be perceived to influence, their work.

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Table 1.- Descriptive data for the dependent variable: Life expectancy at birth, males and females- Years. (1995-2009)

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	79.258	(1.280)	79.250	(78.400,80.100)
BELGIUM	78.328	(1.502)	78.400	(77.400,79.225)
BULGARIA	72.077	(1.051)	72.100	(71.400,72.800)
CYPRUS	78.840	(1.283)	78.900	(77.700,80.100)
CZECH REPUBLIC	75.466	(1.533)	75.500	(74.300,76.600)
DENMARK	78.687	(0.538)	78.700	(78.300,79.000)
ESTONIA	71.513	(1.959)	71.100	(70.100,73.100)
FINLAND	78.651	(1.545)	78.500	(77.400,79.700)
FRANCE	79.529	(1.457)	79.500	(78.500,80.500)
GERMANY	79.540	(0.945)	79.500	(78.800,80.100)
GREECE	78.964	(1.114)	79.100	(78.300,79.700)
HUNGARY	72.259	(1.477)	72.200	(71.175,73.300)
IRELAND	77.823	(1.473)	77.900	(76.200,79.200)
ITALY	80.317	(1.295)	80.300	(79.300,81.300)
LATVIA	71.413	(0.976)	71.100	(70.825,72.175)
LITHUANIA	71.480	(0.945)	71.800	(71.100,72.000)
LUXEMBOURG	78.480	(1.312)	78.000	(77.300,79.500)
MALTA	78.667	(1.045)	78.800	(77.500,79.500)
NETHERLANDS	79.615	(0.971)	79.600	(78.725,80.400)
POLAND	74.205	(1.443)	74.400	(73.025,75.275)
PORTUGAL	76.323	(2.139)	76.400	(74.950,78.200)
ROMANIA	72.837	(0.980)	73.000	(71.950,73.375)
SLOVAKIA	74.154	(1.113)	74.000	(73.300,74.800)
SLOVENIA	78.660	(1.381)	78.600	(77.400,79.700)
SPAIN	79.824	(1.506)	79.800	(78.700,81.000)
SWEDEN	80.063	(0.864)	79.900	(79.500,80.700)
UNITED KINGDOM	79.043	(1.448)	79.100	(78.100,80.000)

Source: Eurostat and own construction

Table 2.- Descriptive data for the dependent variable: Ischemic Heart Disease mortality, males and females. Standardised death rate per 100,000 inhabitants – 3 year average

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	119.293	(23.587)	116.400	(100.375,137.825)
BELGIUM	76.652	(14.225)	79.450	(64.950,83.925)
BULGARIA	151.364	(31.366)	150.400	(124.350,169.250)
CYPRUS	83.929	(9.609)	80.400	(79.600,83.200)
CZECH REPUBLIC	194.024	(36.157)	186.950	(169.475,209.500)
DENMARK				
ESTONIA	306.700	(56.295)	313.750	(254.925,348.475)
FINLAND	149.936	(35.946)	147.800	(124.575,174.775)
FRANCE	42.998	(9.824)	43.350	(37.400,49.375)
GERMANY	115.898	(40.540)	106.900	(92.125,126.575)
GREECE	77.181	(14.547)	75.100	(65.650,86.125)
HUNGARY	239.116	(25.280)	234.600	(219.450,254.875)
IRELAND	136.396	(28.920)	128.450	(111.675,161.700)
ITALY	72.040	(11.595)	70.750	(63.500,80.000)
LATVIA	297.333	(25.607)	291.300	(281.775,315.525)
LITHUANIA	337.175	(21.100)	334.550	(322.575,343.300)
LUXEMBOURG	73.146	(12.855)	76.600	(66.050,78.950)
MALTA	149.838	(22.658)	143.900	(134.575,173.250)
NETHERLANDS	74.925	(20.390)	73.300	(57.100,89.100)
POLAND	115.180	(27.738)	113.250	(89.600,134.400)
PORTUGAL	70.519	(31.803)	63.600	(45.375,87.925)
ROMANIA	222.756	(65.135)	193.300	(177.125,287.425)
SLOVAKIA	266.829	(39.175)	275.200	(252.425,294.325)
SLOVENIA				
SPAIN	58.308	(14.849)	55.900	(47.300,67.500)
SWEDEN	118.223	(21.189)	115.800	(101.000,132.375)
UNITED KINGDOM	126.641	(29.900)	124.300	(104.475,145.300)

Source: Eurostat and own construction

Table 3.- Descriptive data for the dependent variable: Cancer mortality, males and females. Standardised death rate per 100,000 inhabitants - 3 year average

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	168.925	(12.120)	167.050	(159.925, 176.375)
BELGIUM	181.085	(28.325)	183.150	(169.075, 197.600)
BULGARIA	178.567	(32.769)	170.100	(157.300, 183.650)
CYPRUS	124.286	(27.643)	120.000	(108.800, 122.400)
CZECH REPUBLIC	234.582	(29.550)	228.650	(215.675, 246.175)
DENMARK				
ESTONIA	198.292	(3.996)	197.850	(196.275, 202.050)
FINLAND	144.751	(16.585)	144.100	(137.975, 150.025)
FRANCE	173.752	(23.580)	176.550	(162.725, 187.650)
GERMANY	174.224	(27.764)	171.250	(163.000, 180.300)
GREECE	160.672	(23.178)	153.500	(145.375, 168.350)
HUNGARY	257.084	(15.871)	257.400	(245.350, 269.425)
IRELAND	188.946	(10.067)	187.850	(182.000, 197.800)
ITALY	169.671	(20.367)	170.100	(153.000, 183.000)
LATVIA	194.892	(1.369)	195.000	(193.525, 196.100)
LITHUANIA	196.125	(1.851)	195.800	(195.052, 196.725)
LUXEMBOURG	171.400	(14.006)	168.000	(159.250, 180.425)
MALTA	163.254	(12.975)	157.600	(153.400, 171.725)
NETHERLANDS	194.230	(9.990)	192.700	(186.450, 201.950)
POLAND	212.609	(17.686)	216.500	(199.575, 226.675)
PORTUGAL	164.252	(34.997)	158.100	(150.325, 179.325)
ROMANIA	179.820	(20.558)	183.500	(165.150, 192.075)
SLOVAKIA	198.196	(20.728)	205.200	(196.925, 211.025)
SLOVENIA				
SPAIN	164.302	(11.531)	164.500	(156.800, 172.000)
SWEDEN	154.339	(6.761)	154.000	(150.200, 159.250)
UNITED KINGDOM	186.493	(16.1118)	184.200	(173.800, 195.425)

Source: Eurostat and own construction

Table 4.- Descriptive data for the dependent variable: Lung cancer mortality, males and females. Standardised death rate per 100,000 inhabitants – 3 year average

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	37.062	(8.433)	32.900	(30.900,42.450)
BELGIUM	46.915	(8.975)	47.900	(42.075,52.200)
BULGARIA	40.728	(7.799)	37.750	(35.025,42.725)
CYPRUS	32.575	(0.805)	32.150	(32.000,33.550)
CZECH REPUBLIC	50.062	(9.721)	48.150	(43.800,53.150)
DENMARK				
ESTONIA	31.492	(1.864)	30.550	(29.950,33.600)
FINLAND	30.120	(6.781)	27.850	(25.100,37.000)
FRANCE	36.573	(7.307)	36.950	(34.725,39.950)
GERMANY	35.970	(8.037)	36.100	(29.300,40.700)
GREECE	41.430	(6.401)	40.350	(37.700,43.800)
HUNGARY	58.405	(13.725)	63.900	(40.700,70.575)
IRELAND	39.675	(3.354)	38.450	(37.125,42.775)
ITALY	34.965	(8.125)	35.950	(28.025,41.800)
LATVIA	37.113	(2.564)	37.350	(34.525,38.900)
LITHUANIA	21.700	(6.385)	20.900	(18.300,22.400)
LUXEMBOURG	39.625	(1.235)	39.750	(39.150,40.625)
MALTA	80.982	(1.664)	80.800	(80.500,81.600)
NETHERLANDS	47.475	(8.597)	47.500	(44.050,50.675)
POLAND	51.342	(9.370)	52.750	(46.375,57.575)
PORTUGAL	34.034	(17.765)	28.100	(24.200,30.000)
ROMANIA	41.577	(7.398)	41.150	(36.600,43.100)
SLOVAKIA	37.350	(3.746)	37.350	(35.000,40.500)
SLOVENIA	38.205	(6.057)	37.900	(32.100,44.100)
SPAIN	38.466	(4.597)	37.700	(35.600,41.100)
SWEDEN	26.557	(3.427)	26.100	(23.800,29.525)
UNITED KINGDOM	41.414	(10.297)	40.400	(34.425,48.275)

Source: Eurostat and own construction

Table 5.- Descriptive data for the variable: Gross Domestic Product per capita in PPS.

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	29559.259	(5626.535)	30500	(25400,32900)
BELGIUM	23558.788	(9399.397)	20700	(17675,26125)
BULGARIA	6434.444	(2857.875)	5800	(4500,7100)
CYPRUS	18206.667	(3830.417)	18100	(14600,21400)
CZECH REPUBLIC	15670.833	(7002.681)	13800	(11300,16475)
DENMARK	23844	(5007.083)	23600	(20100,27000)
ESTONIA	11300	(3992.878)	10750	(7600,14900)
FINLAND	22856	(6587.155)	22100	(18100,26800)
FRANCE	19103.077	(4953.832)	19200	(15900,21400)
GERMANY	22998.632	(6163.492)	22000	(18950,26425)
GREECE	16657.949	(4135.598)	16300	(13600,19100)
HUNGARY	13580.952	(5455.696)	10.800	(10075,14625)
IRELAND	24250	(8228.368)	22950	(18400,31800)
ITALY	25157.143	(6175.334)	26800	(18800,30200)
LATVIA	9100	(3059.915)	8600	(6400,12000)
LITHUANIA	9666.667	(3352.753)	9100	(6900,12800)
LUXEMBOURG	50080	(12520.224)	49200	(37000,62500)
MALTA	17227.273	(1618.698)	16800	(16200,19000)
NETHERLANDS	25020.556	(6258.025)	24300	(20525,28900)
POLAND	9398.417	(3062.026)	8800	(7200,10800)
PORTUGAL	16174.286	(4610.941)	15500	(12800,18500)
ROMANIA	7251.667	(4206.198)	5850	(4700,8500)
SLOVAKIA	13986	(9116.078)	10400	(7900,16400)
SLOVENIA	17103.33	(4947.621)	16550	(13300,20000)
SPAIN	19640.351	(5556.054)	19300	(15500,23350)
SWEDEN	23947.5	(5565.65)	23400	(19525,26300)
UNITED KINGDOM	22042.018	(8792.323)	20600	(17275,24125)

Source: Eurostat and own construction

Table 6.- Descriptive data for the variable: Gini Index (percentage)

Countries	Mean	sd	Median	(Q1, Q3)
AUSTRIA	25.629	(1.031)	25.900	(25.000,26.200)
BELGIUM	27.743	(1.090)	27.900	(27.000,28.300)
BULGARIA	28.780	(4.453)	26.000	(25.000,33.400)
CYPRUS	28.671	(0.867)	28.800	(28.300,29.100)
CZECH REPUBLIC	25.233	(0.403)	25.200	(25.000,25.300)
DENMARK	23.318	(2.188)	23.900	(21.000,25.100)
ESTONIA	34.030	(1.975)	34.050	(33.100,35.000)
FINLAND	24.914	(1.721)	25.900	(24.000,26.000)
FRANCE	28.167	(1.035)	28.000	(27.000,29.000)
GERMANY	26.967	(2.065)	26.450	(25.000,29.075)
GREECE	33.929	(0.777)	34.000	(33.100,34.700)
HUNGARY	26.489	(2.650)	25.600	(25.000,27.000)
IRELAND	31.421	(1.556)	31.700	(30.000,33.000)
ITALY	31.369	(1.339)	31.500	(31.000,32.200)
LATVIA	36.633	(1.847)	36.750	(35.400,37.700)
LITHUANIA	33.800	(2.094)	34.000	(31.000,35.500)
LUXEMBOURG	27.193	(1.159)	27.200	(26.500,27.800)
MALTA	27.550	(1.307)	27.100	(26.900,27.900)
NETHERLANDS	27.193	(1.156)	27.000	(26.400,27.600)
POLAND	32.071	(1.821)	32.000	(30.000,33.300)
PORTUGAL	36.662	(0.832)	36.800	(36.000,37.000)
ROMANIA	32.270	(2.870)	31.000	(30.000,34.900)
SLOVAKIA	25.460	(1.588)	24.800	(24.500,26.200)
SLOVENIA	22.756	(0.758)	22.700	(22.000,23.400)
SPAIN	32.373	(1.328)	32.000	(31.200,34.000)
SWEDEN	23.260	(1.050)	23.400	(23.000,24.000)
UNITED KINGDOM	32.857	(1.386)	32.450	(32.000,34.000)

Source: Eurostat and own construction

Table 7.- Descriptive data for the explanatory variables.

Explanatory variables	Mean	sd	Median	(Q1, Q3)
Youth male unemployment rate (%)	17.996	(10.093)	16.100	(10.900,22.600)
Youth female unemployment rate (%)	20.072	(13.035)	16.800	(10.100,26.500)
Secondary students (%)	9.757	(1.661)	9.786	(8.751,10.814)
University students (%)	22.105	(3.721)	21.853	(19.581,24.585)
External balance (%)	-1.429	(6.829)	-1.200	(-5.000,3.300)
Public expenditure rate (%)	46.524	(5.582)	46.900	(43.000,51.000)

Source: Eurostat and own construction

Table 8.1.- Results of estimating the models. Fixed effects.

Dependent variables	Life expectancy	Ischemic heart disease crude rate	Cancer standardized rate	Lung cancer crude rate
B	-0.1307(0.0142)** ¹	-0.2630(0.0830)**	-0.3366(0.1407)**	-0.1181(0.0413)**
Fixed effects:				
GDPPC	0.0031(0.0023)	-0.00151(0.0174)	-0.00454(0.0145)	0.00150(0.0017)
GDPPC_1	0.0001(0.0001)	-0.00141(0.0020)	0.00304(0.0018)	-0.00429(0.0020)**
GDPPC_2	-0.0002(0.0001)	0.00146(0.0049)	-0.0038(0.00436)	0.0007(0.0028)
GDPPC rate_1	-0.0068(0.0038)	0.1214(0.0510)**	0.09215(0.0462)	0.0481(0.052)
GDPPC rate_2	0.00055(0.0045)	0.1200(0.0565)**	0.02609(0.0539)	-0.0355(0.0544)
Sec	-0.000004(0.00005)	-0.00145(0.0007)	-0.00183(0.0006)**	-0.00269(0.00075)**
Univ	-0.00003(0.00006)	-0.00004(0.0003)	0.00075(0.0003)**	0.00142(0.00035)**
Pubexp	-0.00007(0.00002)	-0.0045(0.0012)**	0.00045(0.0009)	0.0014(0.00098)
Umy	-0.00002(0.00002)	0.00038(0.00027)	-0.00047(0.0002)**	0.000203(0.00029)
Ufy	0.000007(0.00001)	0.000001(0.00022)	-0.00026(0.0002)	-0.00051(0.00024)**
Bpg	0.00011(0.00004)**	-0.00043(0.0008)	0.00089(0.0007)	0.00205(0.0008)**
Gini	-0.01526(0.0189)	-0.2553(0.2820)	-0.0531(0.3206)	0.02948(0.1091)
Standard deviation of random effects:				
Heterogeneity	0.0461(0.0007)	0.0504(0.0008)	0.0376(0.0008)	0.06362(0.0012)
α_j	0.7777(0.1201)	3.0965(0.4745)	2.6601(0.4717)	0.01068(0.0064)
β_j	0.0759(0.0121)	0.3217(0.0397)	0.4497(0.0679)	0.1800(0.0332)
β_t	0.0031(0.0006)	0.0726(0.0144)	0.2829(0.0537)	0.00625(0.00212)
γ_{gdppc_j}	0.0110(0.0016)		0.0435(0.0117)	
γ_{gdppc_t}	0.0028(0.0005)	0.0347(0.0090)	0.00729(0.0029)	
γ_{gini_j}	0.0271(0.0062)	0.8757(0.1340)	0.8743(0.1449)	0.1942(0.03500)
γ_{gini_t}	0.0040(0.0009)	0.1929(0.0503)	0.3672(0.0781)	0.0067(0.0023)
DIC	-28009.40	-6554.70	-7514.33	-5577.65
Effective number of parameters	2710.75	254.13	303.63	135.88
-log(mean(cpo))	-1.6383	-1.639	-1.6395	-1.6394

¹ mean (standard deviation); the 95% credible interval did not contain the zero (statistically significant).

Source: own construction

Table 8.2.- Results of estimating the models. Random effects¹.

Standard deviation of random effects	Life expectancy	Ischemic heart disease crude rate	Cancer standardized rate	Lung cancer crude rate
α_j		Bulgaria 7.9855(1.4220) Czech Republic -5.9847(1.3797) Finland 9.6170(1.3112) Poland -5.0229(1.4860)	Finland 6.8965(0.9709) Greece -5.4328(1.0596) Portugal 4.1434(1.4078) UK -3.0494(1.0514)	
β_j	Malta -0.0436(-0.0235) ² Portugal 0.0332(0.0163) UK 0.0245(0.0125)	Bulgaria -0.7441(0.1117) Estonia 2.8070(0.1396) Finland -0.5451(0.1025) Greece -1.0776(0.0925) Luxembourg 0.4856(0.1516) Malta 0.3493(0.1596) Netherlands 0.1761(0.0874) Romania 0.3714(0.1053)	Finland -0.7364(0.1173) France 2.6596(0.1234) Greece -1.4436(0.1113) Ireland 0.4454(0.2001) Italy -0.5197(0.1185) Portugal -0.5399(0.1165) Romania 0.4549(0.1315) Spain 0.3640(0.1269) United Kingdom 0.3108(0.1165)	Austria 0.12168(0.0549) Finland -0.1267(0.0637) France 0.0990(0.0447) Greece -0.7050(0.0736) Hungary 0.1225(0.05299) Netherlands 0.0993(0.0503) Poland 0.1283(0.0549) UK 0.0971(0.0438)
β_t	2003 -0.00316(0.0015)	2009 0.2010(0.0279)	2008 -0.2162(0.0986) 2009 0.5854(0.1011)	1999 -0.0131(0.0073) 2008 0.01674(0.0089) 2009 0.02255(0.0101)
$\gamma \text{ gdppc}_j$	Cyprus 0.0129(0.0061) Malta 0.0474(0.0025) Poland -0.00517(0.0026)		Czech Republic -0.05786(0.0245) Greece 0.1038(0.0330))	
$\gamma \text{ gdppc}_t$	1998 0.00050(0.00024) 2003 0.00063(0.00023) 2005 0.00067(0.00024) 2008 -0.0022(0.00072)	2009 0.0870(0.0229)	2008 -0.1255(0.0066) 2009 -0.0230(0.0103)	
$\gamma \text{ gini}_j$	Greece 0.0379(0.01494) Malta -0.0820(0.02891)	Austria 1.1912(0.6014) Bulgaria -1.2913(0.3439) Czech Republic 1.7244(0.3770) Finland -2.1168(0.3354) Greece 0.9246(0.3375) Poland 1.2568(0.3978)	Finland -1.0312(0.2975) Greece 3.3630(0.3162)	Austria -0.1473(0.0606) France -0.1116(0.0485) Greece 0.75553(0.07857) Hungary -0.1449(0.06145) Netherlands -0.11834(0.05614) UK -0.1006(0.0475)
$\gamma \text{ gini}_t$	1996 -0.00477(0.00244) 1998 -0.00429(0.00207) 2009 0.0055(0.00242)	2009 -0.4911(0.0939)	2008 0.3663(0.1407) 2009 -0.7714(0.1451)	1999 0.0128(0.0080) 2006 -0.0137(0.0078) 2007 -0.0166(0.0087)

¹Only those coefficients where the 95% credible interval did not contain the zero (statistically significant); ² mean (standard deviation)

Source: own construction

Figure 1.- Life expectancy at birth (Index, 100 EU-27 average per period)

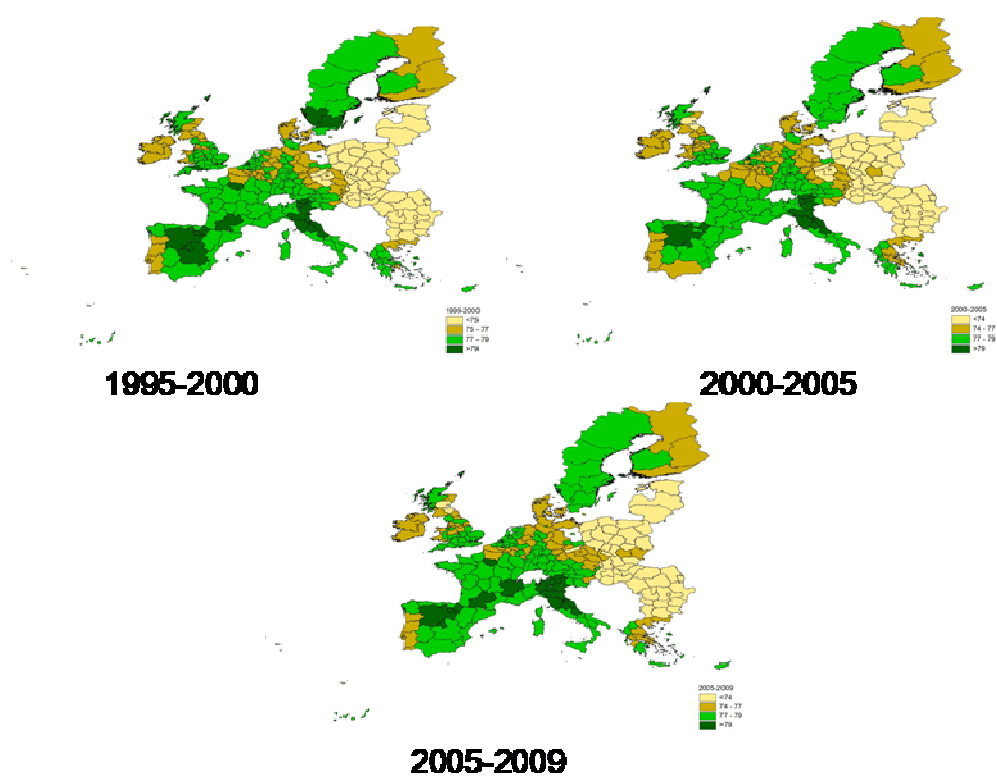


Figure 2.- Ischemic heart mortality (Index, 100 EU-27 average per period)

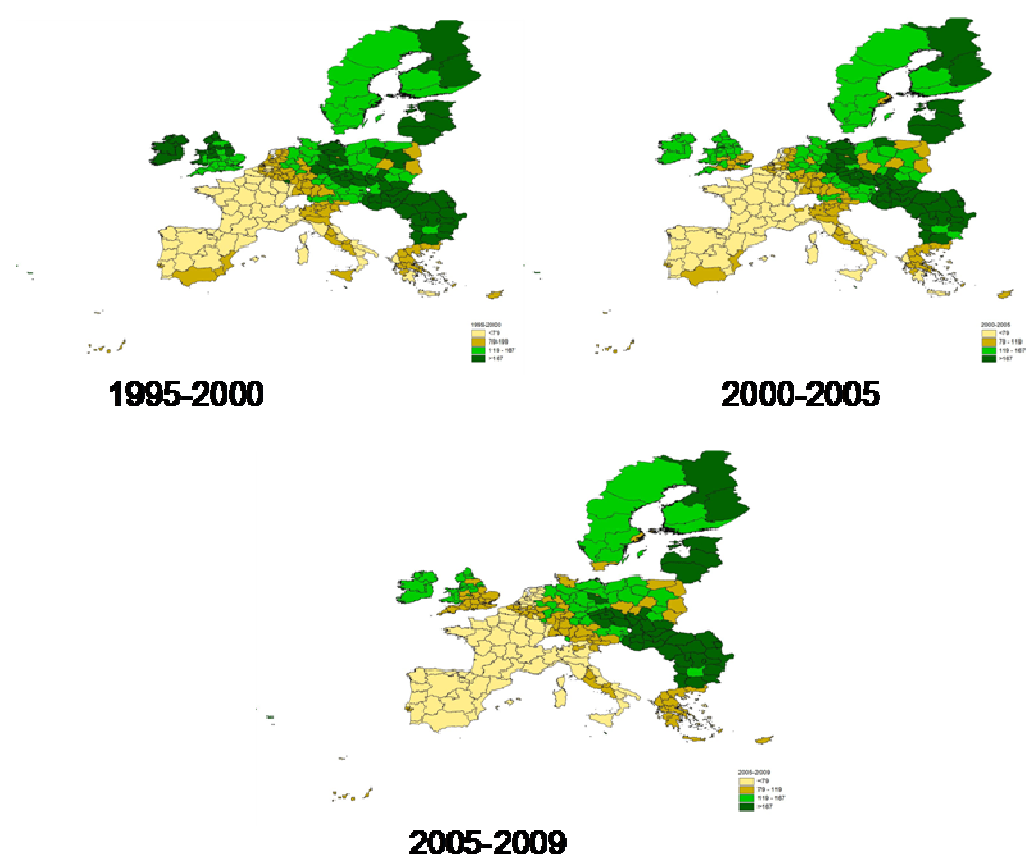


Figure 3.- Cancer mortality (Index, 100 EU-27 average per period)

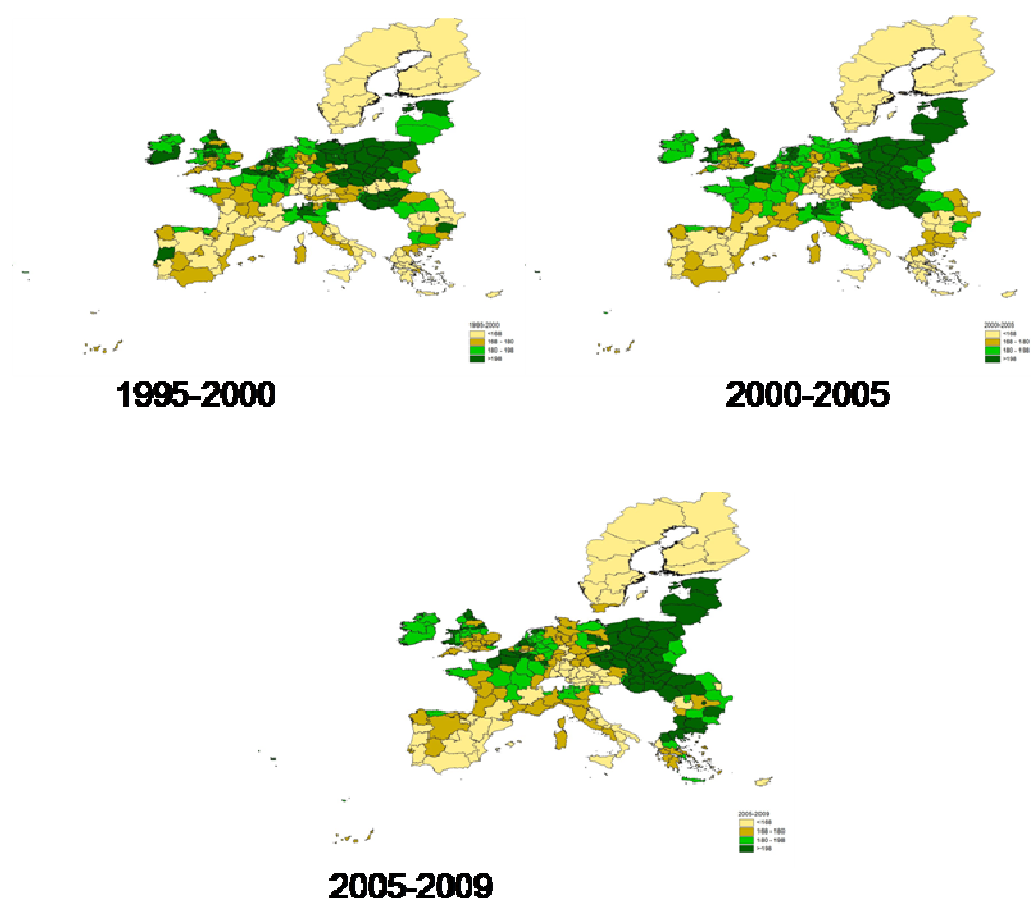


Figure 4.- Lung cancer mortality (Index, 100 EU-27 average per period)

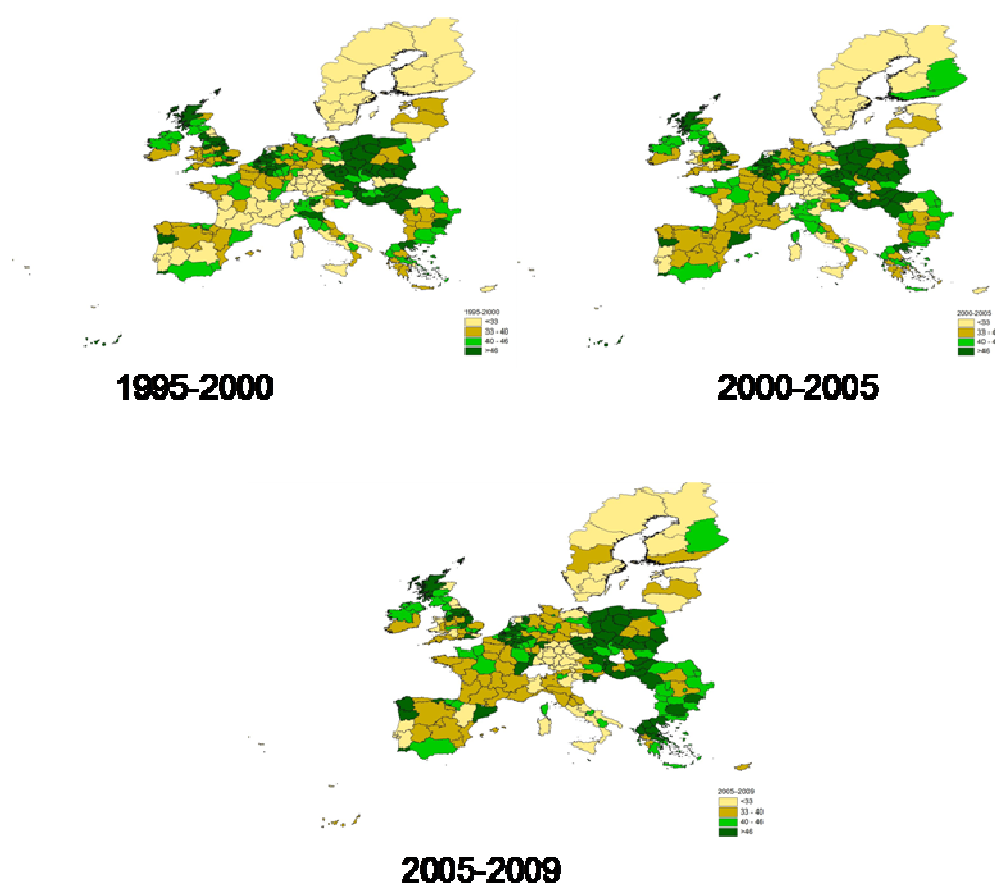


Figure 5.- GDP per capita (quartiles)

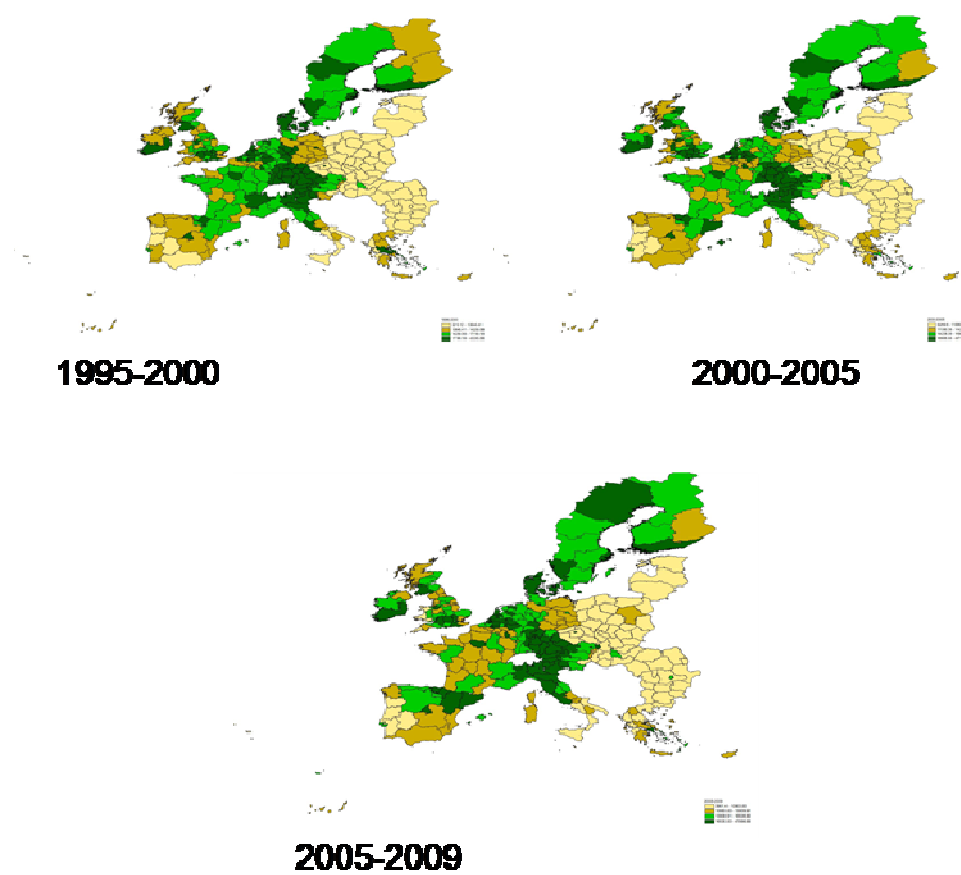


Figure 6.- Gini index (quartiles)

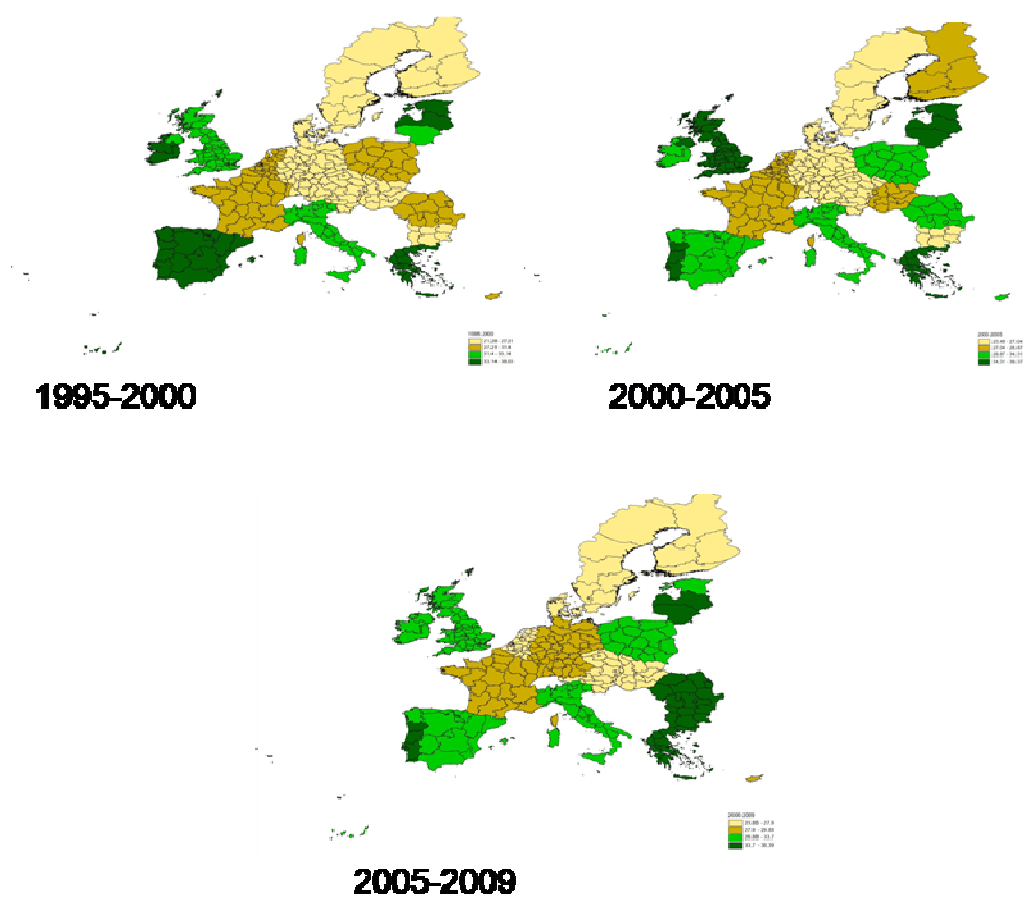


Figure 7.- Sigma convergence. Coefficient of variation in the variable¹ between regions of EU-27.



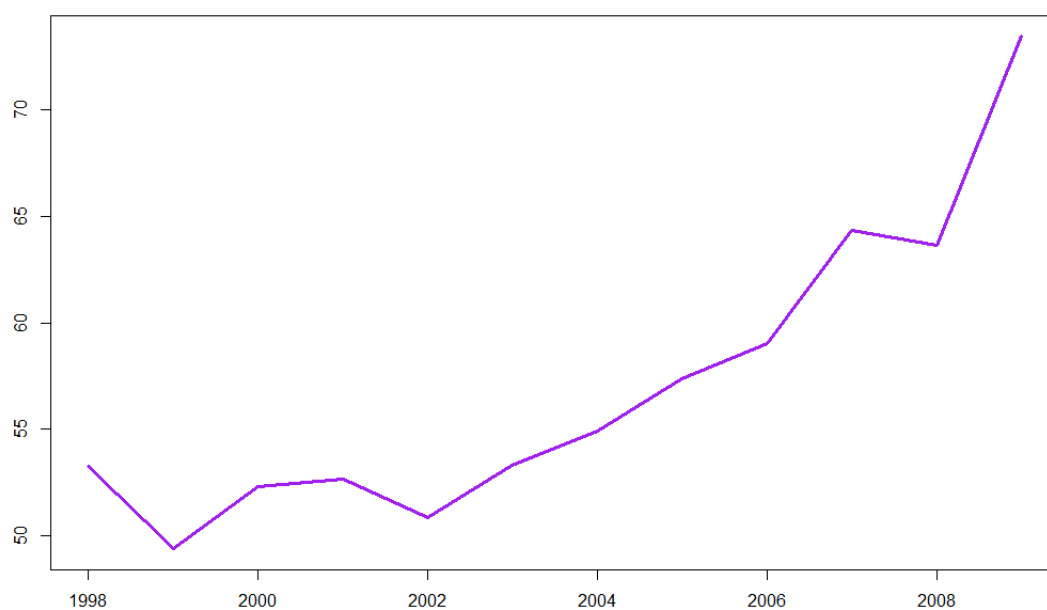
a.- Life expectancy at birth – EU 27



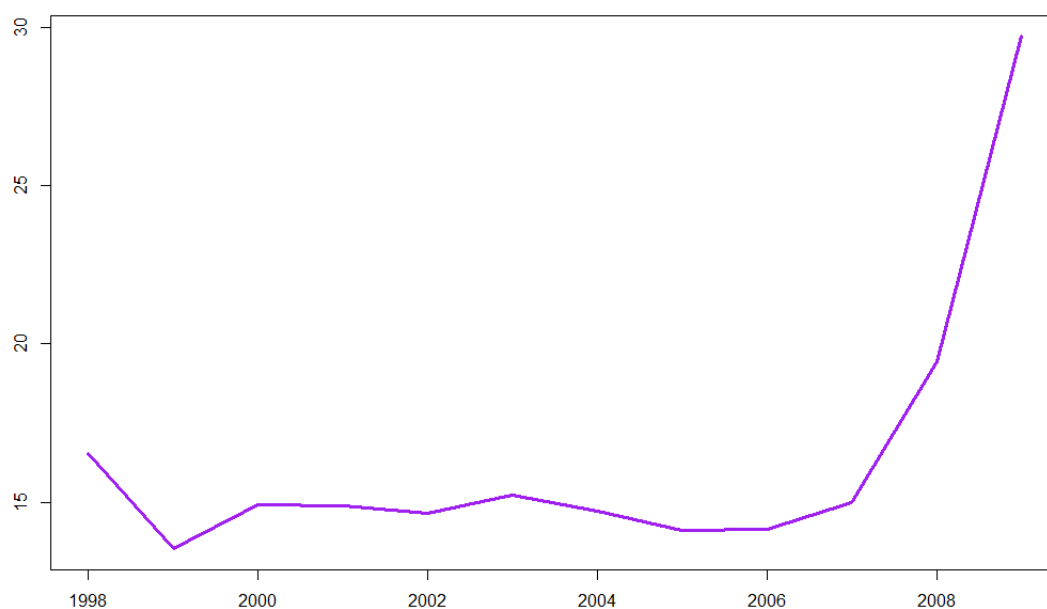
b.- Lung cancer mortality – EU 27

¹ Variable adjusted in the model

Figure 7.- Sigma convergence. Coefficient of variation in the variable¹ between regions of EU-27.



c.- Ischemic heart disease – EU 27



d.- Cancer mortality – EU 2

¹ Variable adjusted in the model



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