Eur J Health Econ
DOI 10.1007/s10198-014-0609-1

ORIGINAL PAPER

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

Laia Maynou · Marc Saez · Jordi Bacaria · Guillem Lopez-Casasnovas

Received: 2 September 2013 / Accepted: 8 May 2014

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 and 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 across both 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.

L. Maynou · M. Saez (✉)
Research Group on Statistics, Econometrics and Health (GRECS), University of Girona, Campus de Montilivi, 17071 Girona, Spain
e-mail: marc.saez@udg.edu
URL: http://www.udg.edu/grecs.htm

L. Maynou · M. Saez
CIBER of Epidemiology and Public Health (CIBERESP), Madrid, Spain

L. Maynou · J. Bacaria
London School of Hygiene and Tropical Medicine, London, UK

M. Saez · G. Lopez-Casasnovas
Center for Research in Health and Economics (CRES), Universitat Pompeu Fabra, Barcelona, Spain

J. Bacaria
Instituto Tecnológico Autónomo de México (ITAM), Mexico, Mexico

G. Lopez-Casasnovas
Department of Economics and Business, Universitat Pompeu Fabra, Barcelona, Spain

G. Lopez-Casasnovas
Barcelona Graduate School (BSGE), Universitat Pompeu Fabra, Barcelona, Spain

Keywords Health convergence · Beta convergence · Sigma convergence · Catching-up · Spatiotemporal modelling · Bayesian models · Integrated nested Laplace approximation

JEL Classification I14 · I15 · C33 · C11

Introduction

Numerous 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 control for all the dimensions of life quality directly. However, it is possible to use summary measures that encompass a wider range of factors of well-being [3, 4].

The main objective of this article is to capture a wider set of dimensions for the quality of life. As a result, in an effort to look beyond income, we analyse convergence using life expectancy and (cause-specific) mortality in the European Union (EU) regions (EU-27) from 1995 to 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 space. Second, we control for spatial correlations across regions. Third, our dataset is more disaggregated because it comprises regions rather than countries, and allows us to develop a more detailed picture of disparity dynamics.

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 as 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 other factors.

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 the rank of each individual in the socioeconomic domain [17]. This index, similarly to the Gini coefficient used in our article, is not without controversy relating to, among other things, 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 outcomes.[1] 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 best known theories 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 article by Felder and Tauchman [33] uses these lasts 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 equalizing 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 well-being or development tend towards one another over time [35].

There are two well-known convergence hypotheses: the absolute convergence hypothesis 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 incomes 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 towards its own equilibrium.

Beta and sigma convergence

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. Quah 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

[1] This was pointed out by one of the anonymous reviewers.

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 virtually the entire world, Preston [42] showed that when income was kept constant, the change in the longevity–income profile represented gains of 15 years in life expectancy. In fact, macroeconomic studies of economic growth, such as that of Barro [43], have already found that life expectancy is a key predictor of economic growth. Pritchett and Summers [44] corroborated this by using instrumental variables, and found 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 health care. Wilson [46] studied the world distribution of life expectancy and found a decrease in its dispersion (i.e. sigma convergence). Becker et al. [6], in a worldwide study examining whether there is a positive correlation between longevity and income per capita, showed that convergence exists with longevity, but not with income. Glei 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 finds that improvements in life expectancy have been greater for developing countries. Similarly, Eggleston and Fuchs [50], studying life expectancy in industrialized countries, point out that most gains in life expectancy have occurred in adult mortality, in particular for those over 65 years.

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 industrialized 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] nor Clark [49] finds (beta) convergence. Finally, d'Albis et al. [52] did not find (beta and sigma) convergence across countries when they considered the entire sample of industrialized countries, but they do provide some evidence of (sigma) convergence among a subset of countries.

The 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 EU-27 regions 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 the EU-15 level and the EU-27 level. However, the speed of convergence is not constant, neither in time nor between regions [53, 55]. With regard to sigma convergence, Monfort [26] shows that convergence between EU-15 regions was strong up until the mid-1990 s and stabilized 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 EU'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 constant neither in time nor between regions.

The rest of this article is organized as follows. First, we explain the method. Then, we explain and discuss the results of the model. Finally, we present our conclusions.

Methods

Data setting

We use data from 271 regions of the 27 EU member countries from 1995 to 2009. Data were 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 27 countries, we have 271 regions).

Econometric model

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

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

where $\mathbf{g}_T$ denotes the vector of the (dependent variable) average growth rate in the period $(0,T)$, $\mathbf{y}_0$ is the vector of the (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 beta-convergence hypothesis (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, beta 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 article, we use the conditional specification of the beta-convergence hypothesis:

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

where $\mathbf{X}$ is a matrix of explanatory variables (of convergence), and γ is the associated (unknown) parameters.

In contrast to more standard studies, we do not specify cross-section models, but rather specify spatiotemporal 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 may have varied during the period under analysis. Furthermore, with small T, we need a large N to obtain consistent estimates.

In particular, we have specified the following model:

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

where y denotes one of the four dependent variables we chose. First, as in most previous studies on health (in concurrence with the seminal article 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]: ischaemic heart disease mortality; cancer mortality; and larynx, trachea, bronchus and lung cancer mortality (cause-specific mortality was standardized as the death rate per 100,000 inhabitants, 3-year average).

Subscript i denotes the region ($i = 1, \ldots, 271$), subscript j denotes the country ($j = 1, \ldots, 27$), subscript t denotes the year ($t = 1995, 1996, \ldots, 2009$), α, β and γ denote unknown parameters, S denotes spatial random effects (see below) and u is the normally distributed disturbance term. Some data are 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 the 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 (gdppc rate). 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 Eurostat [56], the Gini index is defined as the relationship of cumulative shares of the population arranged according to the level of equivalized disposable income to the cumulative share of the equivalized total disposable income received by them. More conveniently, it can be defined as twice the covariance between income and income ranks.[2] 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 by 8 % per 0.05 increase in the Gini coefficient. Furthermore, Kondo et al. also seem to confirm a theoretical 'threshold effect' (a Gini coefficient of 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 at both the regional level and the country level. The panel that we create with these data is unbalanced. Data were not available for all period and for all regions.

For the regional level, we have the following variables:

- umy — Youth male unemployment rate. Unemployment rate (15–24 years old) for young males from 1999 to 2009 as an average for the regions of the EU. For some regions, some data are missing for some years, mainly for the last period.
- ufy — Youth female unemployment rate. Unemployment rate (15–24 years old) for young females 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 (postsecondary non-tertiary education) over the total population from 1999 to 2009. Some data are missing, mainly from Germany, Greece, Spain and UK regions.
- univ — Percentage of university students. Ratio of the sum of level 5 and level 6 students (tertiary education) over the total population from 1999 to 2009. Data are missing also for the same countries as for the variable for secondary students. These countries do not report to Eurostat all data on education.

For the county level, we have the following variables:

- bpg — External balance. The ratio of the value of exported goods minus the value of 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 the value of goods and services bought by the state over the country's GDP. All data available from 1995 to 2009

Three reasons 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, we found these variables are the ones giving us the best model in terms of goodness of fit (deviance information 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,

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

With respect to the other explanatory variables, the random effects are associated with different levels depending on the final model.[3]

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

[2] We appreciate this definition from the other anonymous reviewers.

[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.

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) [64]:

$$\Delta \upsilon_{jt} = \upsilon_{jt} - \upsilon_{jt+1} \quad \Delta \upsilon_{jt} \sim N\left(0, \sigma_{\upsilon}^{2}\right).$$

Spatiotemporal adjustment

In all models, the disturbance terms, although Gaussian, are not identically and independently distributed. In fact, with spatial data, as in our case, it is necessary to distinguish between two sources of extra variability: 'spatial dependence' or clustering, and non-spatial heterogeneity [65, 66]. In our case, as we have the time dimension in our data, there is also temporal dependency (i.e. serial autocorrelation).

To take into account this spatiotemporal 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 is 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. [67], and specify a Matérn structure [68]. In short, we use a representation of the Gaussian Markov random field explicitly constructed through stochastic partial differential equations which has as a solution a Gaussian field with a Matérn covariance function [67].

Inference

To estimate the models we have chosen to use a conditional approach and not a marginal approach, for example, the 'fixed effects model'. There were three reasons for our doing so. First, as is known, the fixed effects estimators eliminate unobserved individual heterogeneity. In fact, we are interested not only in controlling for this heterogeneity but also in modelling it, in particular as regards the coefficient of interest. Second, we use a very complex design with multiple levels (regions, countries) and dimensions (spatial and temporal). This implies the existence of important heterogeneity both in the initial conditions (i.e. intercept), in the coefficient of interest, and in the coefficients associated with the other explanatory variables. Third, and maybe most importantly, in dynamic panel data models the fixed effects estimator is inconsistent, particularly with small T and large N, as in our case. This arises because the demeaning process, which is used to remove individual heterogeneity, creates a non-zero correlation between the regressors and the error [69–71]. The most popular consistent solution in the context of dynamic panel data models is the use of the generalized method of moments (GMM) estimator in first differences, also known as the Arellano–Bond estimator [72, 73], or its extension the 'system GMM' estimator [74]. In dynamic panel data models, however, unless the initial levels of the dependent variables are fixed constants [75], the lagged dependent variable and the error term values are correlated, which leads to inconsistent estimators, even for sufficiently large T and N [62]. This is the known problem of state dependence [76, 77].

In random coefficient dynamic panel data models, with the lagged dependent variable as the explanatory variable and, typically, with finite T, as a consequence, at least, of the state dependence problem, the assumption of independence between the regressors and the random effects does not hold [70, 71]. However, Hsiao et al. [75] show that, even in this case, the use of a Bayesian approach performed fairly well. Under the Bayesian perspective, Zhang and Small [78], building on the estimator of Hsiao et al. [75], allow the initial values to be correlated with the unit-specific coefficients and impose stationarity on the unit-specific AR(1) coefficients. Their approach provides good estimates even when T is small. Maynou and Saez [79] show how the greater flexibility of the Bayesian estimation, a consequence of its hierarchical strategy, leads to better control of the biases associated with dynamic panel data models. This control allows us to obtain estimates of the parameter of interest with less bias and greater efficiency than with other estimators commonly used in dynamic panel data models (in particular, GMM estimates).

Here inferences are performed using a Bayesian framework. This approach 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 [80–82] or in panel data models [62, 75, 83, 84]. Furthermore, only under the Bayesian approach is it 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 article we prefer to relax the assumption of strict exogeneity, allowing a weak exogeneity of the lagged dependent variable, that is, that current shocks affect only future values of the dependent variable [83]. By doing this, we are able to obtain consistent estimates of the parameters of interest (even with fixed T). 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 be achieved only by the space–time adjustment explained above, imposing a certain structure on the original disturbance term.

Table 1 Descriptive statistics of the variables

Variables	Mean	SD	Minimum	Maximum	Number
Life expectancy (years)	78.14	2.81	67.70	83.30	3,286
Ischaemic heart disease mortality	109.49	62.56	18.70	414.20	2,596
Cancer mortality	180.58	30.47	61.10	477.30	2,613
Lung cancer mortality	40.21	10.98	10.20	100.3	2,661
GDP per capita in PPS	19,474.51	8,422.08	3,200	81,400	3,605
Gini index	29.65	3.64	20	39.20	3,339
Secondary students (% of population)	9.76	1.66	4.19	15.16	1,699
University students (% of population)	22.10	3.72	10.53	37.12	1,962
Young male unemployment rate (%)	18	10.09	1.40	60.10	2,601
Young female unemployment rate (%)	20.07	13.04	1.90	78.90	2,529
External balance (%)	−1.43	6.83	−32.40	27.60	3,992
Public expenditure rate (%)	46.52	5.58	31.20	64.90	4,065

From Eurostat and our own construction

PPS purchasing power standards, *SD* standard deviation

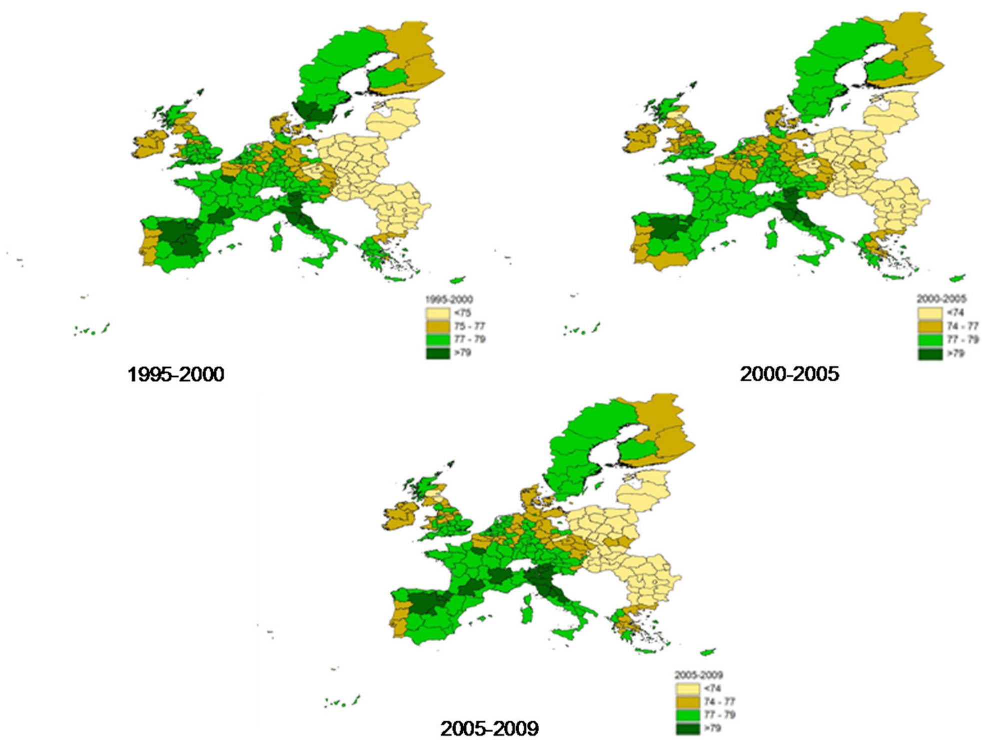

Fig. 1 Life expectancy at birth in three periods: 1995–2000, 2000–2005 and 2005–2009 (index, 100 EU-27 average per period). First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

Within the (pure) Bayesian framework, we follow the integrated nested Laplace approximation approach [85] (see [86] for further details).

All analyses are done with the free software program R (version 2.15.3) [87], though the R-INLA library [64, 85].

Results and discussion

Descriptive

In Table 1, we provide the descriptive statistics of the variables used in the models. This table contains the mean, the standard deviation, the minimum and the maximum value and the number of observations for each dependent and explanatory variable. In addition to this information, we have constructed maps (Figs. 1, 2, 3, 4, 5, 6) showing the evolution of these variables across regions for the study period. Figures 1, 2, 3, 4, 5 and 6 analyse the four dependent variables plus two representative explanatory variables.

Combining the results in Table 1 and the figures, we can explain the evolution of these variables. For our first dependent variable, life expectancy, we can see that regions are moving towards the upper levels. Even if the trend of this variable in all EU countries has been a gradual increase, we find some heterogeneity from 1995 to 2009, ranging from Latvia (mean 71.413) to Italy

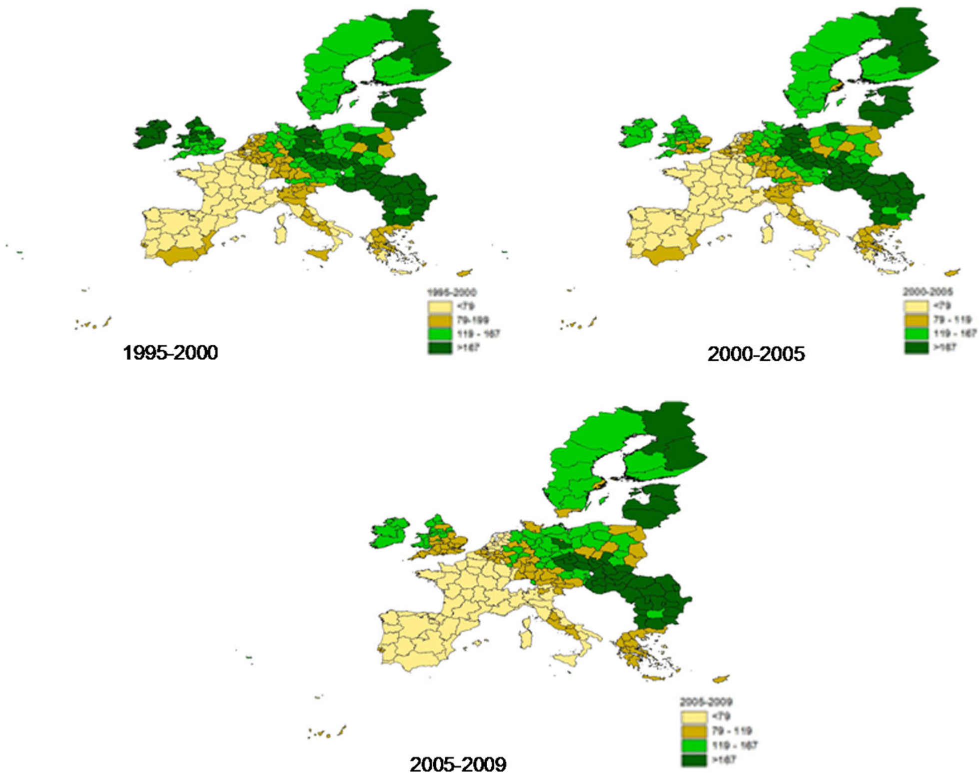

Fig. 2 Ischaemic heart disease mortality in three periods: 1995–2000, 2000–2005 and 2005–2009 (index, 100 EU-27 average per period). First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

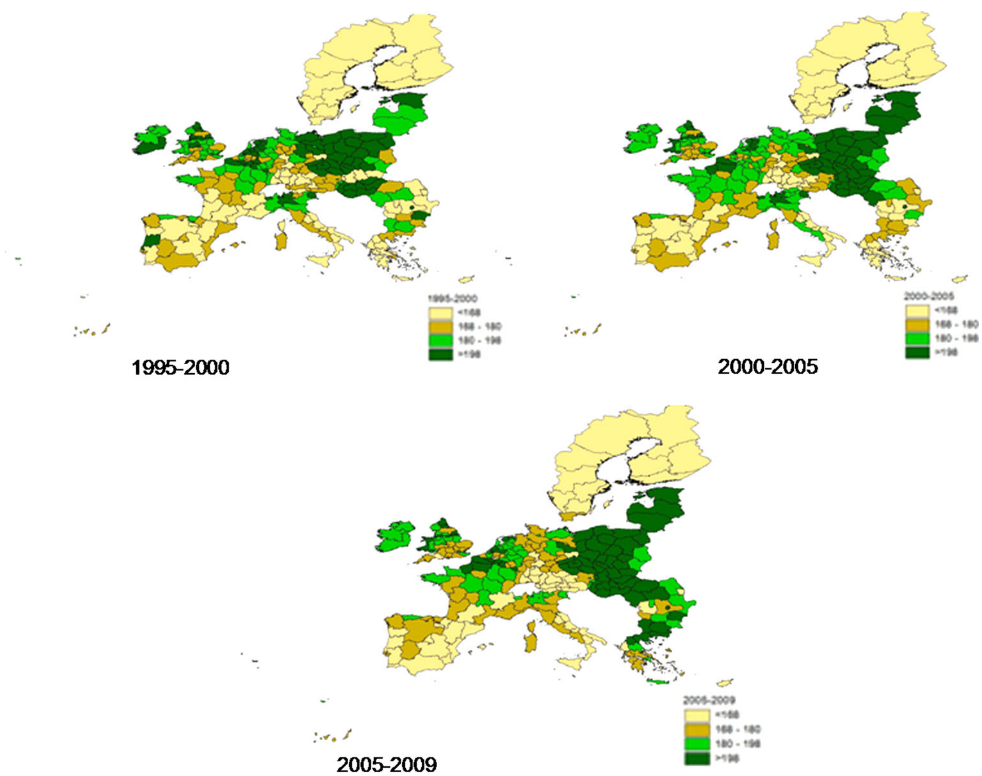

Fig. 3 Cancer mortality in three periods: 1995–2000, 2000–2005 and 2005–2009 (index, 100 EU-27 average per period). First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

(mean 80.317). For ischaemic heart disease mortality and cancer mortality, the common trend in the EU has been a gradual decrease. Eastern European countries have the higher rates for both causes of death, whereas France and Spain have the lowest levels of ischaemic heart disease mortality and Cyprus and Sweden have the lowest levels

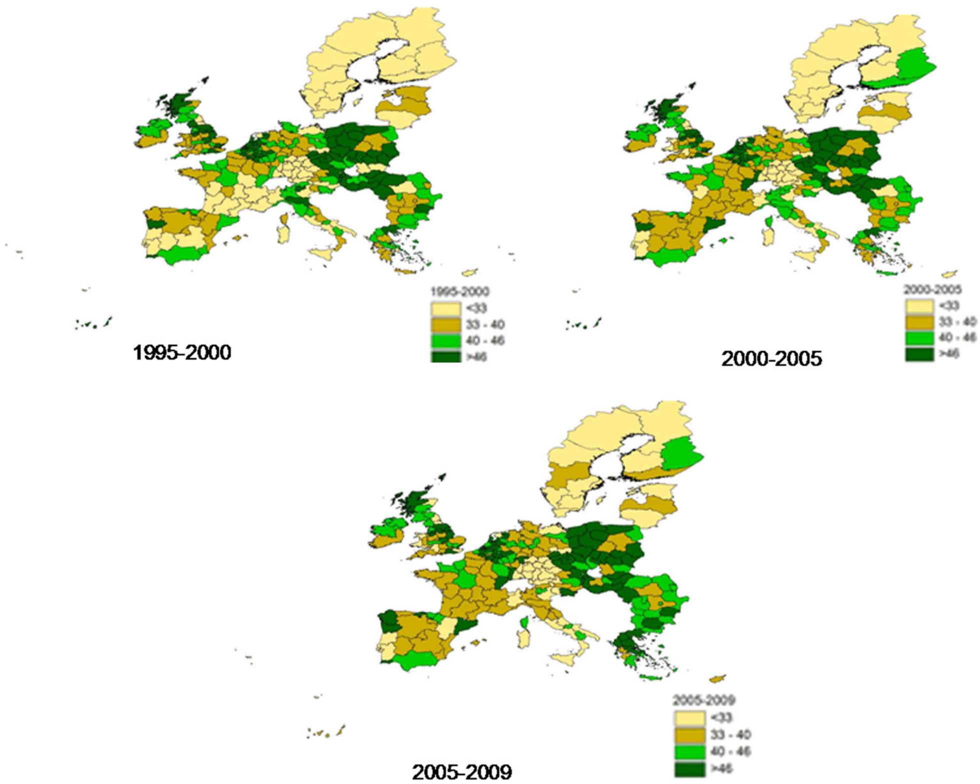

Fig. 4 Lung cancer mortality in three periods; 1995–2000, 2000–2005 and 2005–2009 (index, 100 EU-27 average per period). First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

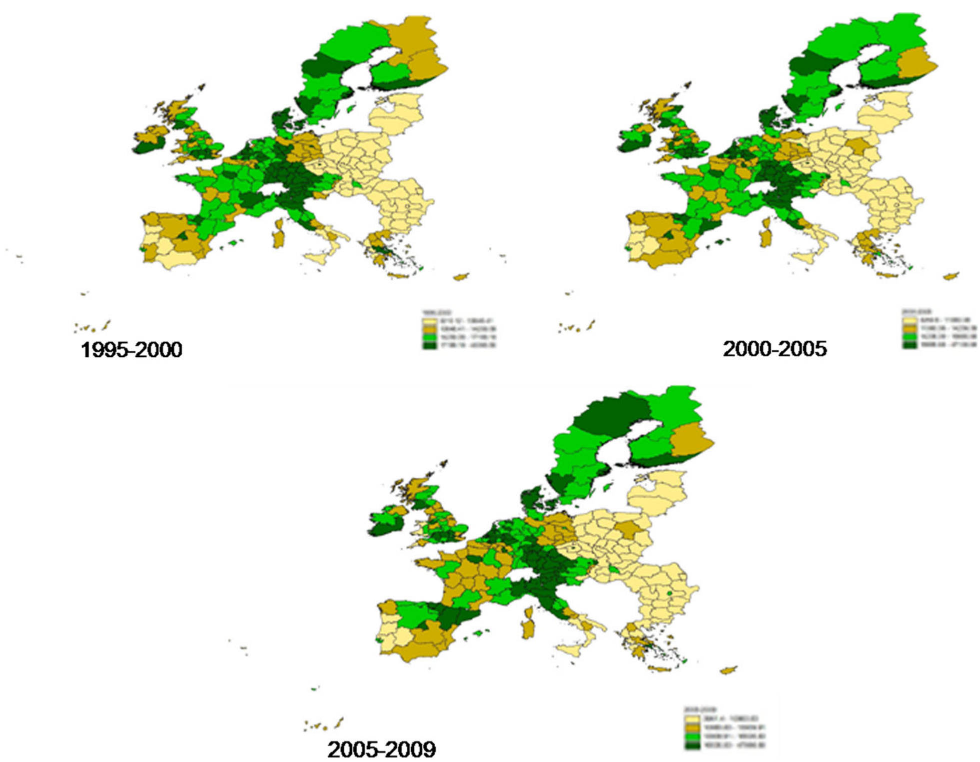

Fig. 5 GDP per capita (quartiles) in three periods: 1995–2000, 2000–2005 and 2005–2009. First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

of cancer mortality. For the last dependent variable, lung cancer mortality, there was no common trend for the EU countries from 1995 to 2009.

GDP per capita and the Gini index are the two other variables represented in the maps. Figure 5 shows that during the period studied, there was a common growth in

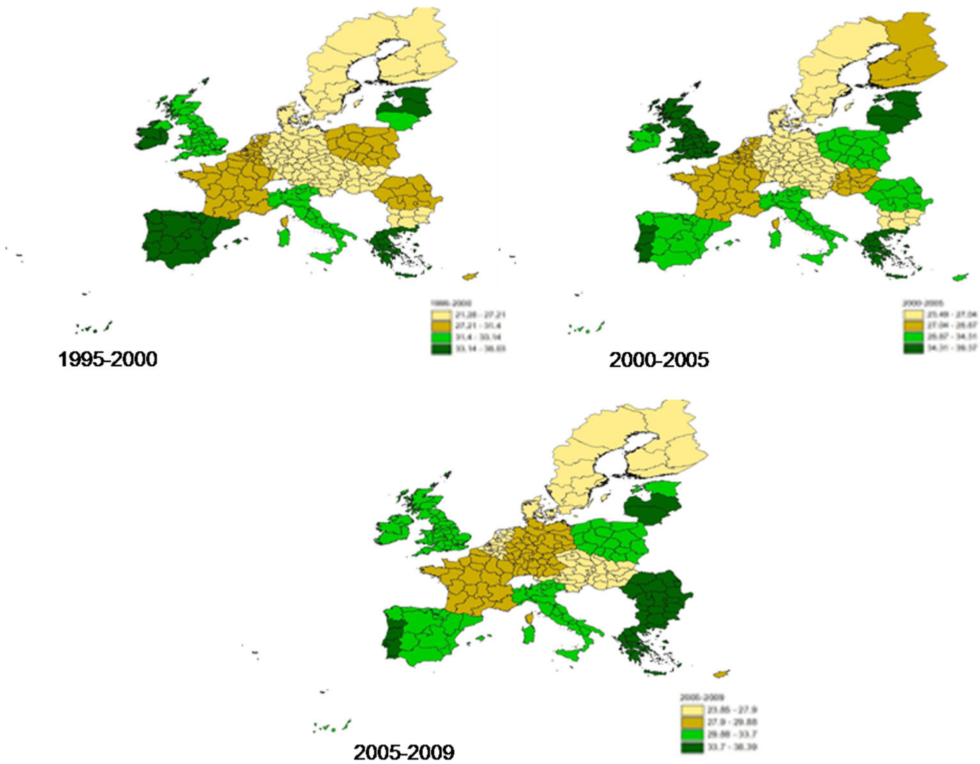

Fig. 6 Gini index (quartiles) in three periods: 1995–2000, 2000–2005 and 2005–2009. First quartile *light yellow*, second quartile *ocher*, third quartile *light green*, fourth quartile *dark green* (colour figure online)

the GDP per capita among all the EU countries. However, although until 2005 some levels rose, after that date some central regions experienced a drop in their GDP per capita. From 1995 to 2009, Luxembourg was the EU country with highest GDP per capita, and Bulgaria had the lowest GDP per capita. In terms of the Gini index, inequalities have increased or decreased in the EU countries, with no common path. The regions with more inequalities were in the east, whereas for the southern and central regions there was a reduction in inequalities from 1995 to 2009.

Results of estimating health convergence models

The results of estimating the models are shown in Table 2. As stated already, 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 [88] to compute the average speed of convergence.[4]

In Table 2, 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 % (i.e., a convergence rate of 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 ischaemic heart disease mortality, we also found convergence between EU countries, as the coefficient of interest was negative, −1.557 %, and statistically significant. In this model, the significant explanatory variables which had an effect on convergence were GDP rates, 0.1214 % (lag 1) and 0.12 % (lag 2), and public expenditure, −0.0045 %. As for standardized 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 males, −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 GDP per capita, −0.00429 % (lag 1), secondary students, −0.00269 %, university students, 0.00142 %, young unemployed females, −0.00051 %, and external balance, 0.00205 %.

Summing up, our results indicate that there was (statistically) significant beta convergence in life expectancy and mortality (ischaemic heart disease, lung cancer and cancer) among the EU-27 regions for the period studied. In particular, the speed of the beta convergence was, on

4 $\frac{-\ln(1-\beta)}{T} \times 100$.

Table 2 Results of estimating the models: fixed effects

Dependent variables	Life expectancy	Ischaemic heart disease crude rate	Cancer standardized rate	Lung cancer crude rate
β	−0.1307 (0.0142)[a]	−0.2630 (0.0830)[a]	−0.3366 (0.1407)[a]	−0.1181 (0.0413)[a]
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)[a]
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)[a]	0.09215 (0.0462)	0.0481 (0.052)
gdppc rate_2	0.00055 (0.0045)	0.1200 (0.0565)[a]	0.02609 (0.0539)	−0.0355 (0.0544)
sec	−0.000004 (0.00005)	−0.00145 (0.0007)	−0.00183 (0.0006)[a]	−0.00269 (0.00075)[a]
univ	−0.00003 (0.00006)	−0.00004 (0.0003))	0.00075 (0.0003)[a]	0.00142 (0.00035)[a]
pubexp	−0.00007 (0.00002)	−0.0045 (0.0012)[a]	0.00045 (0.0009)	0.0014 (0.00098)
umy	−0.00002 (0.00002)	0.00038 (0.00027)	−0.00047 (0.0002)[a]	0.000203 (0.00029)
ufy	0.000007 (0.00001)	0.000001 (0.00022)	−0.00026 (0.0002)	−0.00051 (0.00024)[a]
bpg	0.00011 (0.00004)[a]	−0.00043 (0.0008)	0.00089 (0.0007)	0.00205 (0.0008)[a]
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	−28,009.4	−6,554.7	−7,514.33	−5,577.65
Effective number of parameters	2,710.75	254.13	303.63	135.88
−log(mean cpo))	−1.6383	−1.639	−1.6395	−1.6394

Own construction. The mean is given, with the SD in *parentheses*

cpo conditional predictive ordinate, *DIC* deviance information criterion

[a] The 95 % credible interval did not contain the zero (statistically significant)

average −1.934 % per year for cancer mortality, −1.557 % per year for ischaemic heart disease mortality, −0.819 % per year for life expectancy, and −0.819 % for lung cancer mortality.

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 beta-convergence rate in most of the health variables analysed for 2008 and 2009, 2 years after the start of the economic crisis, might exemplify this.

Table 3 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 as 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. Although there was no divergence in any country, the rate of convergence of life expectancy at birth was less than average in Malta and higher in Portugal and the UK (in that order). As regards ischaemic heart disease mortality, in Estonia, Luxembourg, Romania and Malta (in descending order) there was no convergence

Table 3 Results of estimating the models: random effects

Standard deviation of random effects	Life expectancy	Ischaemic heart disease crude rate	Cancer standardized rate	Lung cancer crude rate
α_j		Bulgaria 7.9855 (1.4220)	Finland 6.8965 (0.9709)	
		Czech Republic −5.9847 (1.3797)	Greece −5.4328 (1.0596)	
		Finland 9.6170 (1.3112)	Portugal 4.1434 (1.4078)	
		Poland −5.0229 (1.4860)	UK −3.0494 (1.0514)	
β_j	Malta −0.0436 (−0.0235)	Bulgaria −0.7441 (0.1117)	Finland −0.7364 (0.1173)	Austria 0.12168 (0.0549)
	Portugal 0.0332 (0.0163)	Estonia 2.8070 (0.1396)	France 2.6596 (0.1234)	Finland −0.1267 (0.0637)
	UK 0.0245 (0.0125)	Finland −0.5451 (0.1025)	Greece −1.4436 (0.1113)	France 0.0990 (0.0447)
		Greece −1.0776 (0.0925)	Ireland 0.4454 (0.2001)	Greece −0.7050 (0.0736)
		Luxembourg 0.4856 (0.1516)	Italy −0.5197 (0.1185)	Hungary 0.1225 (0.05299)
		Malta 0.3493 (0.1596)	Portugal −0.5399 (0.1165)	Netherlands 0.0993 (0.0503)
		Netherlands 0.1761 (0.0874)	Romania 0.4549 (0.1315)	Poland 0.1283 (0.0549)
		Romania 0.3714 (0.1053)	Spain 0.3640 (0.1269)	UK 0.0971 (0.0438)
			UK 0.3108 (0.1165)	
β_t	2003 −0.00316 (0.0015)	2009 0.2010 (0.0279)	2008 −0.2162 (0.0986)	1999 −0.0131 (0.0073)
			2009 0.5854 (0.1011)	2008 0.01674 (0.0089)
				2009 0.02255 (0.0101)
γ gdppc$_j$	Cyprus 0.0129 (0.0061)		Czech Republic −0.05786 (0.0245)	
	Malta 0.0474 (0.0025)		Greece 0.1038 (0.0330)	
	Poland −0.00517 (0.0026)			
γ gdppc$_t$	1998 0.00050 (0.00024)	2009 0.0870 (0.0229)	2008 −0.1255 (0.0066)	
	2003 0.00063 (0.00023)		2009 −0.0230(0.0103)	
	2005 0.00067 (0.00024)			
	2008 −0.0022 (0.00072)			
γ Gini$_j$	Greece 0.0379 (0.01494)	Austria 1.1912 (0.6014)	Finland −1.0312 (0.2975)	Austria −0.1473 (0.0606)
	Malta −0.0820 (0.02891)	Bulgaria −1.2913 (0.3439)	Greece 3.3630 (0.3162)	France −0.1116 (0.0485)
		Czech Republic 1.7244 (0.3770)		Greece 0.75553 (0.07857)
		Finland −2.1168 (0.3354)		Hungary −0.1449 (0.06145)
		Greece 0.9246 (0.3375)		Netherlands −0.11834 (0.05614)
		Poland 1.2568 (0.3978)		UK −0.1006 (0.0475)
γ Gini$_t$	1996 −0.00477 (0.00244)	2009 −0.4911 (0.0939)	2008 0.3663 (0.1407)	1999 0.0128 (0.0080)
	1998 −0.00429 (0.00207)		2009 −0.7714 (0.1451)	2006 −0.0137 (0.0078)
	2009 0.0055 (0.0.00242)			2007 −0.0166 (0.0087)

Own construction. Only those coefficients where the 95 % credible interval did not contain the zero (statistically significant) are shown. The mean is given, with the SD in *parentheses*

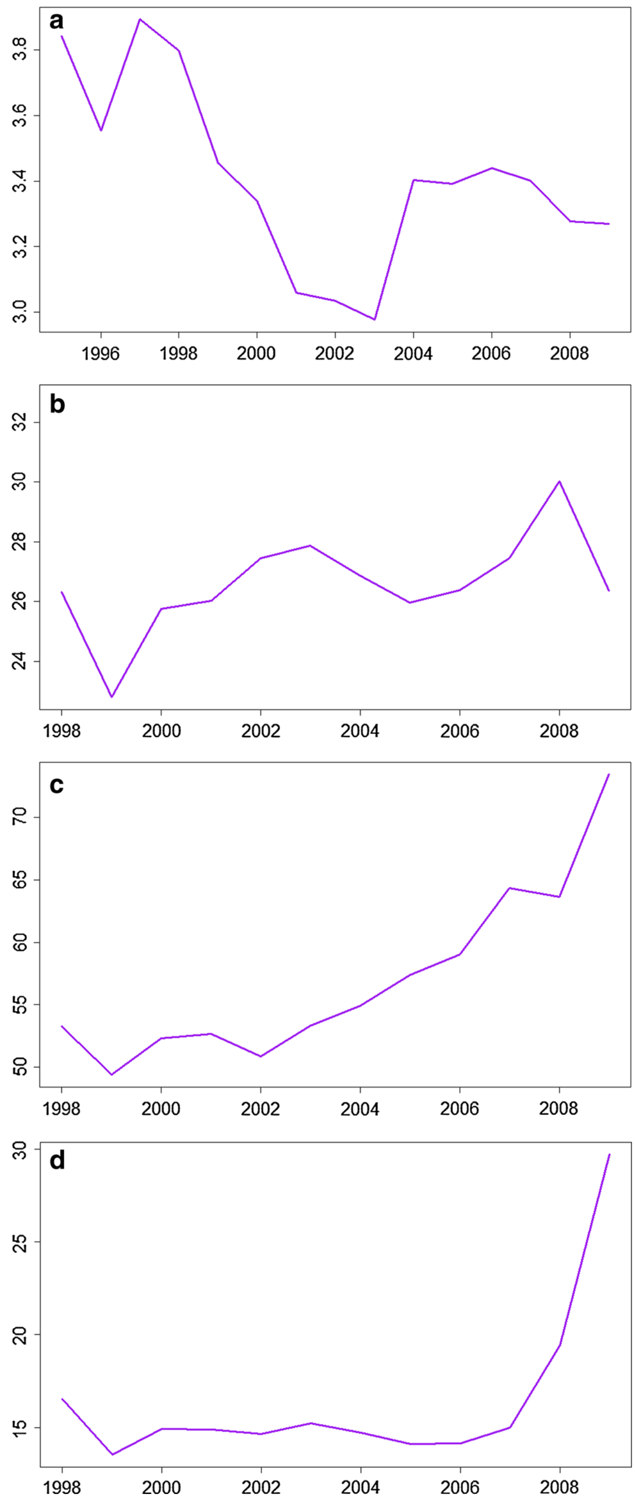

Fig. 7 Sigma convergence. Conditional (computed from the model) coefficient of variation (i.e. standard deviation/mean) between regions of the EU-27. **a** Life expectancy at birth, **b** lung cancer mortality, **c** ischaemic heart disease mortality and **d** cancer mortality

(because the associated coefficient, which was the sum of both the fixed effect and the random effect for that country, was positive). Moreover, even with convergence (because in this case the sum of the fixed effect and the random effect for that country was still negative), it was not as fast as the average for the Netherlands but was faster than that in 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 lung cancer mortality, we estimate a very slight divergence in Poland, Hungary and Austria. Among the converged countries, France and the UK converged at a slower rate and Greece at a much faster than average speed.

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

That is, although we find (beta) convergence on average, we also identify significant differences in the catching-up process across both time and regions. This spatiotemporal heterogeneity is different not only from that 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 phenomena different from 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.

To analyse sigma convergence, we used the coefficient of variation for each health variable (Fig. 7). It is important to note, however, that instead of using the coefficient of variation calculated on the original variables, we used the coefficient of variation calculated on the fitted values from model (3).[5] Note that sigma convergence did not occur in

[5] That is, $CV = E(y_{ijt}) \big/ \left(Var(y_{ijt})\right)^{\frac{1}{2}}$, where both the numerator and the denominator are estimated in model (3). Also note that this calculation can be done easily only 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].

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 15 years. As Sala-i-Martin [36] states, beta convergence is a necessary but not sufficient condition for sigma convergence. 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, whereas 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 able to estimate heterogeneity only at a country level. In previous work on economic convergence between European regions, albeit in a smaller geographic area (the eurozone), we were not able to estimate 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.

Discussion

This work could have several limitations. Let us discuss this 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 owing to a lack of data. In this respect, data for some variables are available at country level up to a maximum of 3 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 number of immigrants from developing countries, are available at a country level for very few countries throughout the entire period considered in this article (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 with 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 the requirements. Once we made the spatiotemporal adjustment, the error terms should be identically and independently distributed. In this sense, we checked the absence of autocorrelation, or spatial or temporal correlation, 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 if the variance of the effects was zero, i.e. if the effects were actually fixed. Only when we rejected this null hypothesis did we maintain the coefficient as a random effect. Furthermore, as regards 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, the conditional autoregressive model, either in its intrinsic version [89] (the between-area covariance matrix is not positive definite) or in its proper version [90] (matrix positive definite). 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 the results are not promising in other sets of circumstances [91]. In fact, as Simpson et al. [92] point out, the conditional autoregressive model relies heavily on the regularity of the lattice, and it is quite difficult to construct a conditional autoregressive model on an irregular lattice that is resolution-consistent [93]. This is the main reason we chose to follow the stochastic partial differential equation 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 area studied, implying a low computational cost and much greater efficiency.

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 and 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 across both time and regions. This last finding differs from the findings of 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, found 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.

Acknowledgments This work was partly funded by the Short Term Grant Abroad for PhD European, CIBER of Epidemiology and Public Health (CIBERESP), Spain, benefiting Laia Maynou, who is also a beneficiary of the Grant for Universities and Research Centres for the Recruitment of New Research Personnel (FI-DGR 2012), AGAUR, Government of Catalonia (Generalitat de Catalunya). We appreciate the comments of the attendees at The Health Economists' Study Group Summer 2013 Conference on 26–28 June 2013 at the University of Warwick, UK, at the New Directions in Welfare III 2013 OECD-Universities Joint Conference on 3–5 July 2013 in Paris, France, and at the 53rd European Regional Science Association on 27–31 August 2013, Palermo, Italy, where a preliminary version of this work was presented. We also appreciate the very valuable comments by the members of the Department of Economics, City University London, UK, and in particular Mireia Jofre-Bonet on a previous version of this article. We appreciate the comments of two anonymous reviewers that, without doubt, helped us improve our work.

Conflict 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 organizations within 3 years of beginning the submitted work that could inappropriately influence, or be perceived to influence, their work.

References

1. Durlauf, S.N., Johnson, P.A., Temple, J.R.W.: Growth econometrics. In: Aghion, P., Durlauf, S.N. (eds.) Handbook of Economic Growth, pp. 555–677. Elsevier, Amsterdam (2005)
2. Kenny, C.: Why are we worried about income? Nearly everything that matters is converging. World Dev. **33**(1), 1–19 (2005)
3. Sen, A.: Mortality as an Indicator of economic success and failure. Econ. J. **108**(446), 1–25 (1998)
4. Sen, A.: Development as Freedom. Random House, New York (1999)
5. Maslow, A.: A theory of human motivation. Psychol. Rev. **50**, 370–396 (1943)
6. Becker, G., Phillipson, T., Soares, R.: The quantity and quality of life and the evolution of world inequality. NBER working paper series, no. 9765 (2003)
7. Mayer, D.: Convergence clubs in cross-country life expectancy dynamics. In: van der Hoeven, R., Shorrocks, A. (eds.) Perspectives on Growth and Poverty, pp. 144–171. United Nations University Press, Tokyo (2003)
8. Wagstaff, A., Paci, P., van Doorslaer, E.: On the measurement of inequalities in health. Soc. Sci. Med. **33**(5), 545–557 (1991)
9. Van Doorslaer, E., Wagstaff, A., Bleichrodt, H., Calonge, S., Gerdtham, U., Gerfin, M., Geurts, J., Gross, L., Häkkinen, U., Leu, R., O'Donell, O., Propper, C., Puffer, F., Rodríguez, M., Sundberg, G., Winkelhake, O.: Income-related inequalities in health: some international comparisons. J. Health Econ. **16**(1), 93–112 (1997)
10. Clarke, P.M., Gerdtham, U.G., Johannesson, M., Bingefors, K., Smith, L.: On the measurement of relative and absolute income-related health inequality. Soc. Sci. Med. **55**, 1923–1928 (2002)
11. Oliver, A., Healey, A., Le Grand, J.: Addressing health inequalities. Lancet **360**, 565–567 (2002)
12. Wagstaff, A.: Inequality aversion, health inequalities, and health achievement. J. Health Econ. **21**, 627–641 (2002)
13. Van Ourti, T.: Socio-economic inequality in ill-health amongst the elderly. Should one use current or permanent income? J. Health Econ. **22**(2), 219–241 (2003)
14. Van Doorslaer, E., Jones, A.M.: Inequalities in self-reported health: validation of a new approach to measurement. J. Health Econ. **22**, 61–87 (2003)
15. O'Donnell, O., van Doorslaer, E., Wagstaff, A., Lindelöw, M.: Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation. The World Bank, Washington (2008)
16. Fleurbaey, M., Schokkaert, E.: Unfair inequalities in health and health care. J. Health Econ. **28**(1), 73–90 (2009)
17. Erreygers, G., Van Ourti, T.: Measuring socioeconomic inequality in health, health care and health financing by means of rank-dependent indices: a recipe for good practice. J. Health Econ. **30**(4), 685–694 (2011)
18. Frick, J., Zeibarth, N.: Welfare-related health inequality: does the choice of measure matter? Eur. J. Health Econ. **14**(3), 431–442 (2013)
19. Wagstaff, A.: Poverty and health sector inequalities. Bull. WTO **80**(2), 97–102 (2002)
20. Wagstaff, A.: The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. Health Econ. **14**(4), 429–432 (2005)
21. Erreygers, G.: Correcting the concentration index. J. Health Econ. **28**, 504–515 (2009)
22. Erreygers, G.: Correcting the concentration index: a reply to Wagstaff. J. Health Econ. **28**, 521–524 (2009)
23. Wagstaff, A.: Correcting the concentration index: a comment. J. Health Econ. **28**, 516–520 (2009)
24. Erreygers, G., Van Ourti, T.: Putting the cart before the horse. Comment on "The concentration index of a binary outcome revisited". Health Econ. **20**, 1161–1165 (2011)
25. Wagstaff, A.: The concentration of a binary outcome revisited. Health Econ. **20**, 1155–1160 (2011)
26. Wagstaff, A.: Reply to Guido Erreygers and Tom Van Ourti's comment on "The concentration index of a binary outcome revisited". Health Econ. **20**, 1166–1168 (2011)

27. Erreygers, G., Clarke, P., Van Ourti, T.: "Mirror, mirror, on the wall, who in this land is fairest of all?"—distributional sensitivity in the measurement of socioeconomic inequality of health. J. Health Econ. **31**, 257–270 (2012)
28. Wennberg, J., Gittelsohn, A.: Small area variations in health care delivery. Science **182**(4117), 1102–1108 (1973)
29. Myrdal, G.: Economic Theory and Underdeveloped Regions. Duckworth, London (1957)
30. Friedmman, J.: Regional Development Policy: A Case Study of Venezuela. MIT Press, Cambridge (1966)
31. Keeble, D., Oxford, J., Walker, S.: Periphery Regions in a Community of Twelve Member States. EC Official Publications, Luxembourg (1988)
32. Krugman, P.: Increasing returns and economic geography. J. Polit. Econ. **99**(3), 483–499 (1991)
33. Felder, S., Tauchmann, H.: Federal state differentials in the efficiency of health production in Germany: an artefact of spatial dependence? Eur. J. Health Econ. **14**, 21–39 (2013)
34. Paas, T., Kuusk, A., Schlitte, F., Võrk, A.: Econometric Analysis of Income Convergence in Selected EU Countries and Their NUTS 3 Level Regions. University of Tartu, Tartu (2007)
35. Barro, R., Sala-i-Martin, X.: Economic Growth. MIT Press, Boston (1991)
36. Sala-i-Martin, X.: The classical approach to convergence analysis. Econ. J. **106**(437), 1019–1036 (1996)
37. Sala-i-Martin, X.: Regional cohesion: evidence and theories of regional growth and convergence. Eur. Econ. Rev. **40**(6), 1325–1352 (1996)
38. Baumol, W.: Productivity growth, convergence, and welfare: what the long run data show. Am. Econ. Rev. **76**(5), 1072–1085 (1986)
39. Barro, R., Sala-i-Martin, X.: Convergence. J. Polit. Econ. **100**(2), 223–251 (1992)
40. Fischer, M., Stirböck, C.: Regional income convergence in the enlarged Europe, 1995–2000: a spatial econometric perspective. ZEW discussion paper no. 04–42 (2004). http://www.econstor.eu/bitstream/10419/24051/1/dp0442.pdf. Accessed 19 Jan 2013
41. Quah, D.: Galton's fallacy and the convergence hypothesis. Scand. J. Econ. **95**, 427–443 (1993)
42. Preston, S.: The changing relation between mortality and level of economic development. Popul. Stud. **29**, 231–248 (1975)
43. Barro, R.: Economic growth in a cross section of countries. Q. J. Econ. **106**(2), 407–443 (1991)
44. Pritchett, L., Summers, L.: Wealthier is healthier. J. Hum. Resour. **31**(4), 842–868 (1996)
45. Anand, S., Ravallion, M.: Human development in poor countries: on the role of private incomes and public services. J. Econ. Perspect. **7**(1), 133–150 (1993)
46. Wilson, C.: On the scale of global demographic convergence 1950-2000. Popul. Dev. Rev. **27**(1), 155–171 (2011)
47. Glei, D.A., Meslé, F., Vallin, J.: Diverging trends in life expectancy at age 50: A look at causes of death. In: Eileen, M., Crimins, S.H.P., Cohen, B. (eds.) International Differences in Mortality at Older Ages: Dimensions and Sources, pp. 103–151. National Academies Press, Washington (2010)
48. Edwards, R.D.: Changes in world inequality in length of life: 1970–2000. Popul. Dev. Rev. **37**(3), 499–528 (2011)
49. Clark, R.: World health inequality: convergence, divergence, and development. Soc. Sci. Med. **72**(4), 617–624 (2011)
50. Eggleston, K.N., Fuchs, V.R.: The new demographic transition: most gains in life expectancy now realized late in life. J. Econ. Perspect. **26**(3), 137–156 (2012)
51. Edwards, R.D., Tuljapurkar, S.: Inequality in life spans and a new perspective on mortality convergence across industrialized countries. Popul. Dev. Rev. **31**(4), 645–674 (2005)
52. d'Albis, H., Esso, L.J., Pifarré, H.: Mortality convergence across high-income countries: An econometric approach. Documents de Travail du Centre d'Economie de la Sorbonne, Université Paris 1, 2012.76 (2012)
53. Monfort, P.: Convergence of EU regions. Measures and evolution. European Union, regional policy working paper 01/2008 (2008)
54. Eckey, H.F., Türk, M.: Convergence of EU-Regions: A literature review. Discussion paper at the Economic Department of the University of Kassel, 86/06, Kassel (2006)
55. Maynou, L., Saez, M., Bacaria, J.: Analysis of regional convergence in the euro area (1990–2010) (in Spanish). Ekonomiaz **82**, 200–217 (2013)
56. Eurostat database http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/database
57. Baumont, C., Ertur, C., Le Gallo, J.: The European Regional Convergence Process, 1980–1995: Do Spatial Regimes and Spatial Dependence Matter? EconWPA series on econometrics, number 0207002 (2002). http://econpapers.repec.org/paper/wpawuwpem/0207002.htm. Accessed 19 Jan 2013
58. Borrell, C., Marí-Dell'olmo, M., Serral, G., Martínez-Beneito, M., Gotsens, M., MEDEA Members: Inequalities in mortality in small areas of eleven Spanish cities (the multicenter MEDEA project). Health Place **16**(4), 703–711 (2010)
59. Puigpinós-Riera, R., Marí-Dell'Olmo, M., Gotsens, M., Borrell, C., Serral, G., Ascaso, C., Calvo, M., Daponte, A., Domínguez-Berjón, F.M., Esnaola, S., Gandarillas, A., López-Abente, G., Martos, C.M., Martínez-Beneito, M.A., Montes-Martínez, A., Montoya, I., Nolasco, A., Pasarín, I.M., Rodríguez-Sanz, M., Saez, M., Sánchez-Villegas, P.: Cancer mortality inequalities in urban areas: a Bayesian small area analysis in Spanish cities. Int. J. Health Geogr. **10**, 6 (2011)
60. Salcedo, N., Saez, M., Bragulat, B., Saurina, C.: Does the effect of gender modify the relationship between deprivation and mortality? BMC Public Health **12**, 574 (2012)
61. Kondo, N., Sembajwe, G., Kawachi, I., van Dam, R., Subramanian, S., Yamagata, Z.: ncome inequality, mortality, and self rated health: meta-analysis of multilevel studies. Br. Med. J. **339**, b4471 (2009)
62. Hsiao, C., Pesaran, M.H.: Random coefficient panel data models. In: Mátyás, L., Sevestre, P. (eds.) The Econometrics of Panel Data. Advances Studies in Theoretical and Applied Econometrics, vol. 46, pp. 185–213. Springer, Berlin (2008)
63. Pinheiro, J.C., Bates, D.: Mixed-Effects Models in S and S-Plus. Springer, New York (2000)
64. R-INLA project http://www.r-inla.org/. Accessed 2 Aug 2013
65. Lawson, A.B., Browne, W.J., Vidal-Rodeiro, C.L.: Disease Mapping with WinBUGS and MLwiN. Wiley, Chichester (2003)
66. Barceló, M.A., Saez, M., Saurina, C.: Spatial variability in mortality inequalities, socioeconomic deprivation, and air pollution in small areas of the Barcelona Metropolitan Region, Spain. Sci. Total Environ. **407**(21), 5501–5523 (2009)
67. Lindgren, F., Rue, H., Lindström, J.: An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach (with discussion). J. R. Stat. Soc. Ser. B **73**(4), 423–498 (2011). http://www.math.ntnu.no/~hrue/spde-jrssb.pdf. Accessed 19 Jan 2013
68. Stein, M.L.: Statistical Interpolation of Spatial Data: Some Theory for Kriging. Springer, New York (1999)
69. Nickell, S.: Biases in dynamic models with fixed effects. Econometrica **49**(6), 1417–1426 (1981)
70. Anderson, T.W., Hsiao, C.: Estimation of dynamic models with error components. J. Am. Stat. Soc. **76**, 598–606 (1981)
71. Anderson, T.W., Hsiao, C.: Formulation and estimation of dynamic models using panel data. J. Econom. **18**, 47–82 (1982)

72. Arellano, M., Bond, S.: Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. **58**, 277–297 (1991)
73. Holtz-Eakin, D., Newey, W., Rosen, H.S.: Estimating vector autoregressions with panel data. Econometrica **56**, 1371–1395 (1988)
74. Blundell, R., Bond, S.: Initial conditions and moment restrictions in dynamic panel data models. J. Econom. **87**, 115–143 (1998)
75. Hsiao, C., Pesaran, M.H., Tahmiscioglu, A.K.: Bayes estimation of short-run coefficients in dynamic panel data models. In: Hsiao, C., Lee, L.F., Lahiri, K., Pesaran, M.H. (eds.) Analysis of Panels and Limited Dependent Variables Models, pp. 268–296. Cambridge University Press, Cambridge (1999)
76. Heckman, J.: Heterogeneity and state dependence. In: Rosen, S. (ed.) Studies in Labor Markets. University of Chicago Press, Chicago (1981)
77. Heckman, J.: Statistical models for discrete panel data. In: Manski, C.F., McFadden, D. (eds.) Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge (1981)
78. Zhang, P., Small, D.: Bayesian inference for random coefficient dynamic panel data models. Department of Statistics, The Wharton School, University of Pennsylvania (2006). http://www-stat.wharton.upenn.edu/~dsmall/randomcoefficientmodel_submittedversion.pdf. Accessed 26 Jul 2013
79. Maynou, L., Saez, M.: Bayesian Estimation of Small Dynamic Panel Data Models. Research Group on Statistics, Econometrics and Health (GRECS), University of Girona, Girona (2013)
80. Raftery, A.: Bayesian model selection in social research. Sociol. Methodol. **25**, 111–163 (1995)
81. Fernández, C., Ley, E., Steel, M.: Model uncertainty in cross-country growth regressions. J. Appl. Econom. **16**, 563–576 (2001)
82. Sala-i-Martin, X., Doppelhofer, G., Miller, R.: Determinants of long-term growth: a Bayesian averaging of classical estimates (BACE) approach. Am. Econ. Rev. **94**(4), 813–835 (2004)
83. Moral-Benito, E.: Determinants of economic growth: a Bayesian panel data approach. Documento de trabajo 1031. Banco de España, Madrid (2010)
84. Rendon, S.R.: Fixed and random effects in classical and Bayesian regression. Oxf. Bull. Econ. Stat. **75**(3), 460–476 (2012)
85. Rue, H., Martino, S., Chopin, N.: Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations (with discussion). J. R. Stat. Soc. Ser. B **71**, 319–392 (2009). http://www.math.ntnu.no/~hrue/r-inla.org/papers/inla-rss.pdf. Accessed 19 Jan 2013
86. Blangiardo, M., Cameletti, M., Baio, G., Rue, H.: Spatial and spatio-temporal models with R-INLA. Spat Spatiotemporal Epidemiol. **4**, 33–49 (2013)
87. R Development Core Team. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna (2012). http://www.R-project.org. Accessed 9 Dec 2012
88. Šlander, S., Ogorevc, M.: Labour costs convergence in the EU: spatial econometrics approach. Privred. Kret. Ekon. Polit, **122**, 27–51 (2010). http://www.hrcak.srce.hr/file/80468. Accessed 26 Jan 2013
89. Besag, J.: Spatial interaction and the statistical analysis of lattice systems (with discussion). J. R. Stat. Soc. Ser. B **36**, 192–236 (1974)
90. Cressie, N.A.: Statistics for Spatial Data. Wiley, New York (1993)
91. Kelsall, J., Wakefield, J.: Modeling spatial variation in disease risk: a geostatistical approach. J. Am. Stat. Assoc. **97**(459), 692–701 (2002)
92. Simpson, D., Illian, J., Lindgren, F., Sørbye, S.H., Rue, H.: Going off grid: Computationally efficient inference for log-Gaussian Cox processes. Preprint statistics no. 10/2011. Norwegian University of Science and Technology, Trondheim (2011). http://www.r-inla.org/papers. Accessed 23 Mar 2013
93. Rue H, Held L. Gaussian Markov Random Fields. Chapman & Hall/CRC, Boca Raton (2005)