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Evolution of life expectancy at birth in French *départements* over the period 1833-1982

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Abstract This paper deals with spatial aspects of trends in life expectancy at birth in the French metropolitan *départements* over the 19th and 20th centuries. Data from the censuses conducted from 1833 to 1982 were used to calculate the life expectancy at birth for both sexes togheter, e_0 . The overall fertility index (*If*), marital fertility index (*Ig*) and nuptiality index (*Im*) were also calculated for each five-year period within the same time span. The analysis has two facets: a first, descriptive part in which we establish clusters of *départements* with similar or different patterns of evolution over the period above mentioned; and a second part in which the effect of covariables in changes in e_0 are examined. In addition their coefficients were interpreted including the direct and spatial spillover effects. Unlike earlier studies, in which a spatio-temporal analysis was performed, the time function showing changes in e_0 is reduced to a single value which measures the distance or affinity between the functions of time in each *département*, which enables us to carry out an exploratory spatial data analysis (ESDA) and apply spatial econometric models.

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1 Introduction

The increase in life expectancy over the last two centuries has been shown to be a worldwide phenomenon, even though it is more striking in western countries. France is a classic example of this, but it is also a vast country with considerable geographical diversity, which is accompanied by major socio-economic differences between regions. Geographical differences in mortality in France have already been the object of major research studies although these publications generally cover short periods of time, and do not apply modern statistical techniques including spatio-temporal analysis: Nizard and Prioux (1975): 1961-1969; Bonneuil (1997): 1806-1906; Lincot and Lutinier (1998): 1975-1994; Gaimard (2005): 1946-1999; Daguet (2005): 1954-1999; Barbieri (2013): 1976-2008. This research shows that levels of mortality vary substantially across the country; some of these differences have evened out in recent years among women, but there are still large differences for men.

Barbieri (2013) founds that mortality is lower in Paris, the south-western *départements* of le-de-France, and Rhne-Alpes and Midi-Pyrnes and that geographical variations in life expectancy at birth are closely linked to variations in mortality above age 30. Nizard and Prioux (1975) and Barbieri (2013) also analyzed the main causes of excess mortality (cancer, suicide, alcoholism, diseases related to the respiratory system, etc.).

One of the aims of our study is to examine the differences in life expectancy at birth for the different *départements* over as long a period as possible (1833-1982) in order to gain a better historical perspective on the changes that took place, with the application of spatial analysis techniques for the first time. Our study is innovative in that it is based on life expectancy data calculated for the 19th century by Bonneuil (1997) complemented by our own calculations for the 20th century.

Geographical diversity is reflected in life expectancy at birth, which, as we shall see, varies considerably across the country. But differences in life expectancy overall are also compatible with the presence of similarities in the patterns observed in neighboring areas; this is the underlying idea in what is known as the First Law of Geography: *"everything is related to everything else, but near things are more related than distant thing"*, defined by Tobler in 1970 (Tobler, 1970).

In this article, we apply spatial exploratory analysis to a large database containing the life expectancy at birth, e_0, both sexes together, in the French *départements*. Our aim is to detect the patterns of spatial clusters and the presence of spatial spillover effects in e_0 and its relationships with the indices of overall fertility (If), marital fertility (Ig) and nuptiality (Im) in the metropolitan French *départements* over the period 1833-1982.

Various spatial and spatio-temporal statistical methods have been applied to the study of life expectancy and mortality in different countries, although they have all been used in the context of very recent time period: for Poland, Malczewski (2010): 2001-2002; for Greece, Tsimbos et al. (2011, 2014): 1998-2005; for Hungary, Bálint (2012): 2005-2009; for the USA, Yang et al. (2015); Sparks and Sparks (2010); Brazil (2015): 1998-2009; for West Africa, Balk et al. (2004): 1997-2001. Windenberger et al. (2012) applied spatial analysis techniques to analyse mortality in the French cantons from 1997 to 2001. Padilla et al. (2013, 2016), working on the period 2002-2009, also applied this type of analytical technique to child and infant mortality. In short, among these studies there is a striking absence of analyses with a longer historical perspective even in those countries where it is easier to obtain historical demographic data. We consider that this article can make a major contribution to improving the state of the question in this field of research.

Historical demographers are still in disagreement over the role played by mortality in the historic decline in fertility. One of the Princeton European Fertility Proyect's main conclusions was that we cannot deduce from the data gathered for the provinces in Europe that the declines in mortality led to the subsequent fall in fertility (Van de Walle (1986): 233). Many other researchers have reached the same conclusions (Watkins (1986): 436; Knodel (1974): 167-185; Lesthaeghe (1977): 171-176; Haines (1998)). In a study on the state of the question concerning the transition and the theory of fertility, (Van de Kaa (1996): 409) concluded: "Notestein's notion that a mortality reduction would automatically lead to a significant decline in fertility through a series of pre-existing social mechanisms is untenable". More recent studies that use modern econometric techniques have also shed light on the negligible role of declining mortality in accounting for falling fertility (Doepke, 2005; Fernndez-Villaverde, 2001; Murphy, 2009). Nonetheless, on the basis of aggregated and individual data, many authors have stressed the special role played by mortality in the fertility transition (Mason, 1997; Galloway et al., 1998; Cleland, 2001; Reher and Sanz-Gimeno, 2007; Dyson, 2010; Van Poppel et al., 2012; Schellekens and Van Poppel, 2012). Recently, Angeles (2010) and Angeles (2015), Herzer et al. (2012)), Murtin (2013) and **?** (anonymized authors reference) (this is a paper already accepted to be published in Demographic Research), using panel data analyses covering long time periods, have shown that mortality rates are a statistically significant predictor of total fertility rates.

Angeles (2015) found that the effect of mortality on fertility was not homogeneous throughout the different phases of the transition. In the pre-transitional stage the relationship was clearly negative: when mortality was high, women needed to use all their fertile years to have children. As the transition progressed and mortality rates underwent a certain improvement, the effect of mortality on fertility became less negative or even zero. As Angeles (2015):13 states that, "the effect may even become positive if some additional mechanism is in place, such as hoarding or the quantity-quality tradeoff, which would make net fertility directly a function of mortality rates".

It is well known that from the earliest data available, dating from the 19th century, up to the 1980s, there was an upward trend in the intensity of nuptiality (*Im*) in western Europe, especially after 1930 (Hanal, 1965; Watkins, 1986)[1]. One question that should concern us now is whether nuptiality varied as a result of changes in mortality. It would be logical to assume that the French *départements* with the highest death rates would compensate for this by allowing a larger percentage of women to get married, so that there would be a positive correlation between the two variables. Some authors have described this as the social effect: societies have their own customs and mech- anisms for ensuring a balance between mortality and fertility. In demographic situations with high mortality, societies have to develop ways of allowing early access to marriage in order to ensure that the population does not decline. Wrigley (1978) tells us that an unconscious rationality probably operated to guarantee the well-being of the group. The relationship between nuptiality and mortality could have constituted an adaptation mechanism that the societies of the past used to regulate population growth.

It is logical to think that in the pre-transitional phase (with high mortality), *départements* with the highest death rates would have higher nuptiality. The maintenance of the population was somehow ensured by making sure that young people had access to marriage (and therefore reproduction) in places where mortality was high. Once the transition was over and mortality no longer played a leading role, we may expect that access to marriage were conditioned by other indicators such as, for example, the availability of employment which would enable young people to set up home.

Despite the huge volume of academic publications on this issue, our paper is of special interest for two reasons: on one hand, because of the considerable historical scope of our data, since the data cover a long period of time, and on the other hand, because we have introduced a distance for each of the original variables which summarizes the joint evolution over time of a *département* and its neighbors with respect to this variable.

The article is organized as follows: in Sections 2 and 3 the source of data and the methodology used for our analysis are described; Section 4 reports the results when these techniques are applied to our data, while Section 5 presents a discussion of these results and some conclusions.

2 Data and methods

The values for life expectancy at birth in the 19th century for the French *départements* were taken from Bonneuil (1997). He obtained the values of e_0 (taking both sexes together) for all the five-year periods from 1806-10 up to 1901-05 (both included). We built the life tables for each sex and for the different *départements* for the following periods: 1910-12, 1920-22, 1930-32, 1945-47, 1953-55, 1966-69 and 1981-83. To do so, we used census data and the mean

[1] Only in the cases of Italy and, especially, Spain, was this general increase in the nuptiality indicators interrupted at the end of the 20th century by several years of contraction.

number of deaths for the three years around the different census years[2] We have 22 cross-sectional observations from an unevenly spaced time series. Fifteen of these observations are from the period 1833-1903 and 7 from 1911-1982. The observations become particularly sparse after 1946. To test the reliability of our calculations, we compared our results for the whole of France with those from the Human Mortality Database, 2014 (http://www.mortality.org/). The differences turned out to be very small, and so we are confident that our estimated values for e_0 in the different *départements* are correct[3].

For the analyzed period (1833-1982) we also have complementary information from the different *départements* concerning other demographic data. In concrete, we obtained the values for what are known as the Princeton fertility indices - overall fertility (I_f), marital fertility (I_g) and nuptiality (I_m). They were obtained from Coale and Watkins (1986) for the years 1831, 1836, 1841, 1846, 1851, 1856, 1861, 1866, 1871, 1876, 1881, 1886, 1891, 1896, 1901, 1911, 1921, 1931 and 1961 (data available from the University of Princeton Website: http://opr.princeton.edu/archive/pefp/). We calculated these indices for 1946, 1968 and 1982.

This set consisting of three indices (I_f, I_g and I_m) was devised especially for the Princeton European Fertility Project to provide measures that could be easily calculated for most populations given the paucity of data needed to calculate more precise fertility and nuptiality measures. Ansley Coale (Coale and Watkins, 1986) was the intellectual architect of this project, which examined the historical decline in marital fertility over more than a hundred years in the 700 provinces of Europe. I_f is the index of the rate of childbearing by all women regardless of their marital status; it is the ratio of the actual number of births to the hypothetical number if women were subject to the married Hutterite fertility schedule (the Hutterites are a Protestant sect, Anabaptists, founded in the sixteenth century. To escape persecution for their beliefs, they emigrated to the northern mid-west of the USA in the nineteenth century. Hutterite women have high fertility because contraception and abortion are forbidden and mothers only breastfeed for a few months). I_g (index of marital fertility) is the ratio of the number of births occurring to married women to the number that would occur if married women were subject to maximum fertility (married Hutterite women). I_m (nuptiality index) is an index of the proportion of potentially fertile women who are currently married; it is the ratio of the number of births currently married women would experience if subject to Hutterite fertility to the number of births all women would experience if subject to Hutterite fertility. This index is not a measure of fertility but rather an index of nuptiality. It is a fertility-weighted aggregate index of marriage that

[2] We took into account the mean number of deaths found around the census year in order to avoid the problem of possible random variations associated with sparsely populated *départements*.

[3] For example, the life expectancy at birth for men in France as a whole in the year 1931 calculated by the Human Mortality Database at Berkeley University is 54.52 years. Our calculations give the figure 54.64 years. That is, the difference between the two is only 0.22%. Similar results were obtained for other years and both sexes.

gives more weight to the proportions married at the prolific ages (less than 30) than at the less prolific ages. The values of Im go from zero (no married woman) to one (all married women aged 15 to 49). See Coale and Watkins (1986):153-162 for information on how the Princeton indices are calculated.

The Princeton indices are widely used in historical demography. We thought that it would be interesting to find out the spatio-temporal connections between the fertility and nuptiality rates and the life expectancy at birth over the whole of our period of analysis. These indices are easily accessible from the webpage of Princeton University, mentioned above, and cover a large period of time and a vast number of provinces. One of the reasons why we confined our time period to the years 1833-1982 was that it is not advisable to calculate the Princeton indices when the percentage of births outside marriage becomes very high (in France, it was 14% in 1982 and 54% in 2010). For similar reasons, there is no point in calculating the index of nuptiality I_m when a large percentage of couples live together without being married (if cohabiting couples are registered on the census as single, the value of index I_m will be seriously affected)

2.1 Data interpolation

As we have pointed out, the 20th century is less represented than the 19th century. While for the latter we have data from 15 equidistant years over periods of 5 years (here we include the year 1903), for the 20th century we only have 7 years without any periodicity. To extend the five-year periods to the latter, we have interpolated the data from each *département* by cubic splines and evaluated the resulting functions every five years from 1908 to 1978. We thus have 30 five-year data-sets between 1833 and 1978. We have added the data available for 1982, even though it does not meet the criteria of the five-year period. In short, we have 31 annual observations for each *département*.

2.2 Measuring spatial autocorrelation

To carry out an exploratory spatial data analysis, we need a neirghborhood structure over the *départements* of metropolitan France. We consider a queen neirghborhood structure with a row standardized connectivity matrix W whose elements are, $w_{ij} = 1/n_i$, if j is a neighbour of i and where n_i is is the total number of neighbours of i. In this neirghborhood structure no *département* is neighbor of itself and consequently $w_{ii} = 0$. The details can be found in Cliff and Ord (1973).

In order to determine whether our data show spatial autocorrelation we use the global Moran index I (Moran, 1950a,b). This index can be interpreted as the regression coefficient between the observed value in a *département* and the mean of the observed values in its own neighborhood. Under the hypothesis of randomness of the spatial distribution of the observed values plus asymptotic normality, we can obtain its expected value, $E(I) = -1/(n-1)$, and its variance. This enables us to built a test to check the existence of spatial autocorrelation. Nonetheless, there is an alternative Montecarlo test based on random permutations which makes it possible to circumvent the problem of asymptotic normality. Both tests were implemented in the spdep package in R Bivand et al. (2012). If there is no spatial autocorrelation the mean of the values in the neighborhood of a *département* will not vary systematically with the value on it. However, if there is a positive association, high or low values in a *département* will be surrounded by similar values. In the notation which has become usual in this context, if L and H denote, respectively, values that are Lower (L) or Higher (H) than the mean, the four combinations HH, HL, LL and LH are possible, in which the first letter refers to the value in a *département* and the second, the mean of the values in its neighborhood.

In 1995 Anselin (Anselin, 1995) introduces the concept of *Local Indicators of Spatial Association* (LISA) to decompose the *Moran I* into its local components, which makes it possible to identify relevant observations and outliers. For a location i, it defines I_i using the following formula:

$$I_i = \frac{(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2/n} \sum_j w_{ij}(x_j - \bar{x}). \quad (1)$$

The values for I_i represent the components of I because the following relationship is easily established, $\sum_i I_i = nI$, where n is the total number of *départements*. The use of I_i to compare the presence of significant local associations runs into difficulties because we do not know its exact distribution, and because there is a correlation among them due to the overlap between the neighbors of different locations, which means that we need to apply corrections such as the Bonferroni correction, False Discovery Rates (*fdr*) or such like. As in the case of I, there is a Montecarlo test provided in the spdep package for R Bivand et al. (2012). In practical terms, the significant values for I_i can be interpreted as follows:

- $I_i > 0$ *cluster* with similar values in the location and its neighbors (H-H, L-L).
- $I_i < 0$ *outlier* with different values in the location and its neighbors (H-L, L-H)

2.3 Data transformation

Our data can be analyzed from a spatio-temporal perspective. However, our present aim is not to conduct such an analysis, but to detect clusters of *départements* which have experienced similar or opposite time evolution. How can we use the data to this end? Our procedure is the following,

1. We obtain, for each one of the four variables, the matrix of distances between the *départements* i and j, $i = 1, \ldots, n,\ \ j = 1, \ldots, n$. As we use *Euclidean* and *Manhattan* distances, two distance matrices will be obtained for each variable. If x is any of our four variables, we must recall that

$$\text{Euclidean } d_{ij} = \left[\sum_{k=1}^{31} (x_{ik} - x_{jk})^2\right]^{\frac{1}{2}}$$

$$\text{Manhattan } d_{ij} = \sum_{k=1}^{31} |x_{ik} - x_{jk}|.$$

2. Once the matrix of distances D have been obtained, the vector $d = diag(D \times W^t)$ provide us with the mean distance of each *département* to its neighbors. W^t stands for the transpose of W.

When we apply the calculation of these distances to e_0, If, Ig and Im, the resulting mean distances d_{e_0}, d_{If}, d_{Ig} and d_{Im} measure the similarity of temporal behavior between one *département* and its neighbors. By using this procedure, we can reduce the 31 time values of each variable associated with each *département* to a single value. We have a dependent variable d_{e_0}, on which we perform only one spatial analysis, given that, by means of the transformation we have carried out, the time factor is no longer present, and three independent variables, d_{If}, d_{Ig} and d_{Im} whose influence will be analyzed subsequently. It is important to interpret these distances appropriately when evaluating future results: they indicate if the temporal evolution of a *département* has been similar to that of its neighbors with respect to the variable associated with the distance. Finally, it must be pointed out that, as in all summaries, there is some information loss. This will be discussed in our conclusions.

3 Spatial regression

The multiple linear regression model (OLS) has the form

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k x_k + \varepsilon \tag{2}$$

where y is the variable for response, x_k, $k = 1, \ldots, p$ the independent variables used to model the behavior of y, and ε represents the error, a random variable which accounts for the discrepancies between the observed values of y and those obtained with the fitted model. We may observe that the model (2) ignores the spatial structure of the data, in particular the relations of neighborhood between the components of the spatial structure where the data were obtained. If, through the exploratory analysis described above, the existence of spatial dependency between observations is detected, it will be necessary to introduce it into (2) in the form of a spatial autoregression term which affects the dependent variable or the error.

3.1 Spatial lag model

The first model takes the form,

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k x_k + \rho W y + \varepsilon. \quad (3)$$

This is different from model (2) because it includes the term Wy which represents the mean of the values of y observed in its neighborhood, W being the matrix of neighborhood. This model is intended to reflect the influence on an observation of what happens in its neighbors. A positive value of ρ indicates that y increases due to this influence, always assuming that ρ is significantly different from 0.

The model is also known as *spatial autoregressive model* by analogy to the AR models in time series in which the temporal autocorrelation is modeled by including time lags, y_{t-k}, in the model for the dependent variable.

3.2 Spatial error model

The second model is expressed as

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k x_k + \lambda W \varepsilon + \epsilon. \quad (4)$$

This model assumes that the errors in model (2) are spatially autocorrelated.

Both spatial models might seem similar at first sight, since both suggest the existence of spatial dependence between observations. However, models (3) and (4) have very different implications. The spatial autoregressive model is a simultaneous model with feedback between observations: the influence of y_i on its neighbors in turn influences y_i through the mean of all these values, Wy. On the other hand, in the spatial error model, dependency appears only through the terms of error, which can be interpreted as the influence of non-observed variables which, for some unknown reason, are spatially correlated.

4 Results

The division of metropolitan France into *départements* is shown in Figure 1. The units in the axes correspond to UTM coordinates. This structure do not correspond to the current one, but to the situation prior to 1968, because that year the *départements* Seine and Seine-et-Oise, both in the le de France region, were subdivided to give rise to the current administrative structure. As the data from before 1968 reflect the earlier *départements*, we have used that structure and made the necessary corrections to the data from the post-1968 period. Also, the *département* of Moselle has been omitted from the analysis due to the lack of data for the lengthy period in which it belonged to Germany.

Also Corsica has been eliminated because it is an island and therefore has no neighbors in the sense defined for this study. We have worked with a total of 88 *départements*.

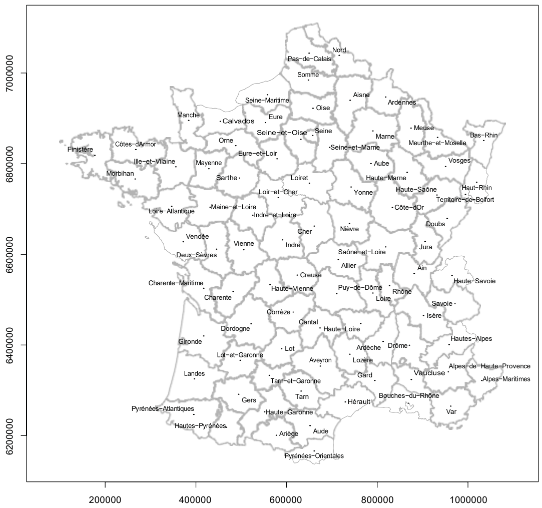


Fig. 1 Division of metropolitan France into *départements*.

Table 1 shows the means, standard deviation and the variation coefficient for each year for the four variables, e_0, If , Ig and Im, obtained for all the French *départements*. The improvement in life expectancy at birth referred to in the Introduction is quite patent. The time evolution of the corresponding standard deviation, sd, is striking, as it falls drastically over these two hundred years. Both fertility indices show a similar decreasing behaviour but their standard deviation do not fall so drastically. The marriage rate has a constant increasing trend throughout the 19th century, which is maintained in the 20th century but with sudden changes that intersperse decreasing periods which seem to consolidate in last times. All these aspects can be observed more easily in Figure 2, in which the semiamplitude of the error bars is the standard deviation for the corresponding year. The dotted line in the graphs stands for the year 1900.

4.1 Exploratory spatial analysis

Figure 3 shows the spatial distribution of d_{e_0} in the French *départements* for the two types of distance. The Moran indices associated with these two spatial distributions are shown in Table 2, and both confirm the existence of spacial autocorrelation.

Table 1 Time evolution for the four variables

	expected life at birth			fertility index overall			fertility index marital			nuptiallity index		
year	mean	sd	cv	mean	sd	cv	mean	sd	cv	mean	sd	cv
1833	37.05	6.539	0.177	0.302	0.038	0.125	0.560	0.106	0.189	0.518	0.066	0.128
1838	39.44	7.384	0.187	0.291	0.036	0.125	0.535	0.104	0.194	0.522	0.065	0.125
1843	41.00	6.218	0.152	0.287	0.037	0.129	0.523	0.102	0.196	0.527	0.065	0.124
1848	38.84	6.035	0.155	0.280	0.037	0.133	0.507	0.100	0.198	0.533	0.066	0.124
1853	38.55	6.157	0.160	0.276	0.038	0.137	0.495	0.106	0.215	0.535	0.070	0.131
1858	38.05	9.550	0.251	0.273	0.037	0.134	0.487	0.107	0.219	0.540	0.072	0.134
1863	40.16	8.065	0.201	0.278	0.039	0.142	0.495	0.119	0.241	0.541	0.074	0.137
1868	40.58	4.787	0.118	0.276	0.039	0.142	0.494	0.123	0.249	0.541	0.075	0.138
1873	38.10	5.235	0.137	0.276	0.040	0.145	0.492	0.124	0.252	0.543	0.074	0.136
1878	42.86	5.622	0.131	0.276	0.042	0.153	0.490	0.130	0.265	0.548	0.073	0.134
1883	42.84	5.962	0.139	0.273	0.043	0.158	0.479	0.129	0.269	0.552	0.074	0.134
1888	44.36	4.828	0.109	0.262	0.043	0.162	0.456	0.125	0.274	0.556	0.072	0.130
1893	44.84	4.413	0.098	0.249	0.040	0.161	0.430	0.116	0.269	0.556	0.069	0.125
1898	47.65	3.820	0.080	0.240	0.038	0.158	0.414	0.111	0.268	0.555	0.068	0.123
1903	48.19	3.570	0.074	0.233	0.036	0.154	0.398	0.105	0.263	0.561	0.065	0.116
1908	50.95	3.356	0.066	0.220	0.035	0.157	0.353	0.086	0.244	0.596	0.059	0.099
1913	53.40	3.274	0.061	0.208	0.032	0.153	0.326	0.071	0.218	0.599	0.054	0.090
1918	53.74	2.675	0.050	0.200	0.027	0.136	0.336	0.066	0.197	0.556	0.049	0.089
1923	54.69	2.269	0.041	0.195	0.026	0.133	0.332	0.064	0.192	0.549	0.050	0.091
1928	56.98	2.148	0.038	0.191	0.028	0.146	0.304	0.059	0.195	0.594	0.052	0.088
1933	58.43	2.101	0.036	0.196	0.027	0.136	0.296	0.051	0.172	0.623	0.046	0.073
1938	58.54	1.849	0.032	0.209	0.026	0.122	0.321	0.048	0.149	0.609	0.036	0.059
1943	59.22	1.597	0.027	0.222	0.028	0.128	0.351	0.054	0.155	0.588	0.039	0.067
1948	62.47	1.386	0.022	0.228	0.024	0.106	0.355	0.045	0.127	0.600	0.032	0.053
1953	67.53	1.381	0.020	0.226	0.024	0.108	0.334	0.036	0.108	0.641	0.028	0.044
1958	70.57	1.422	0.020	0.221	0.029	0.131	0.320	0.041	0.129	0.659	0.035	0.053
1963	71.40	1.294	0.018	0.215	0.026	0.120	0.316	0.037	0.119	0.649	0.030	0.046
1968	71.58	1.154	0.016	0.205	0.021	0.102	0.309	0.031	0.100	0.628	0.023	0.037
1973	72.33	1.069	0.015	0.191	0.018	0.094	0.289	0.026	0.091	0.612	0.021	0.034
1978	73.67	1.018	0.014	0.173	0.016	0.093	0.259	0.022	0.086	0.602	0.022	0.036
1982	74.93	1.015	0.014	0.158	0.016	0.101	0.231	0.021	0.090	0.595	0.026	0.043

Table 2 Moran indices for the spatial distribution of the distances associated with e_0

distance	Moran I	p-value
Euclidean	0.3066	9.466×10^{-7}
Manhattan	0.2858	3.972×10^{-6}

4.1.1 LISA and cluster map for $\mathbf{d_{e_o}}$

The local decomposition of Moran indices in Table 2 into the corresponding LISA was obtained using the function *localmoran* in the spdep package. Positive LISA values, which yield a significant p-value, enable us to detect the clusters of *départements* shown in Figure 4, with the maps corresponding to the two measures. The groupings for H-H and L-L are color-coded, with the centers of the clusters shown in darker colors. As can be seen, there are hardly any differences between the clusters obtained using the two distances.

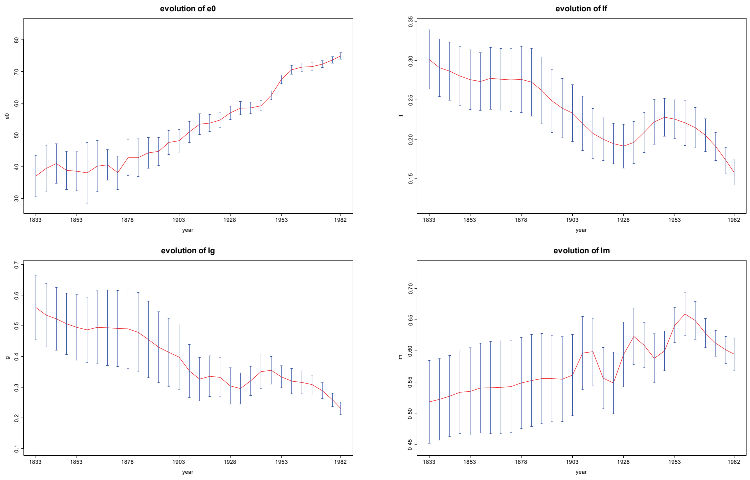


Fig. 2 Time evolution of mean and standard deviation for the four variables.

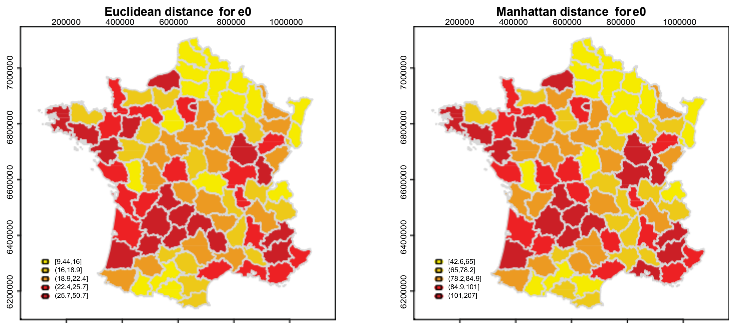


Fig. 3 Spatial distribution of distances associated with e_0 in the French *départements*.

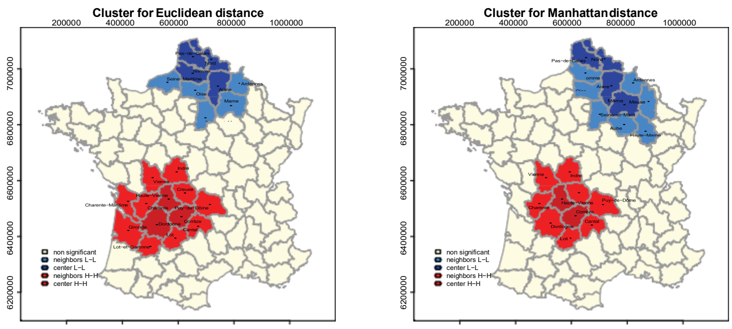


Fig. 4 Clusters of *départements* for the distances associated with e_0.

Tables 12 to 15 in Appendix 1 provide a summary of the information about the clusters. For each type of cluster, H-H or L-L, the tables show the center of the cluster, its neighbors, the value for the distance in the center of the cluster (d_{e_0}) and the mean distance in its neighbors ($\overline{d_{e_0}}$). It should be noted that since the clusters are made up of neighboring *départements*, the centers and neighbors can easily be confused, resulting in a macrocluster with several centers.

The H-H cluster in Figure 4 is located in the west-center of the country and, if we recall how the distances were obtained, means that these *départements* followed very different evolution over time. The L-L cluster, situated in the north of the country, consists of *départements* with a similar evolution over time. Figure 5 shows the different behavior of e_0 in the *départements* forming these two large clusters.

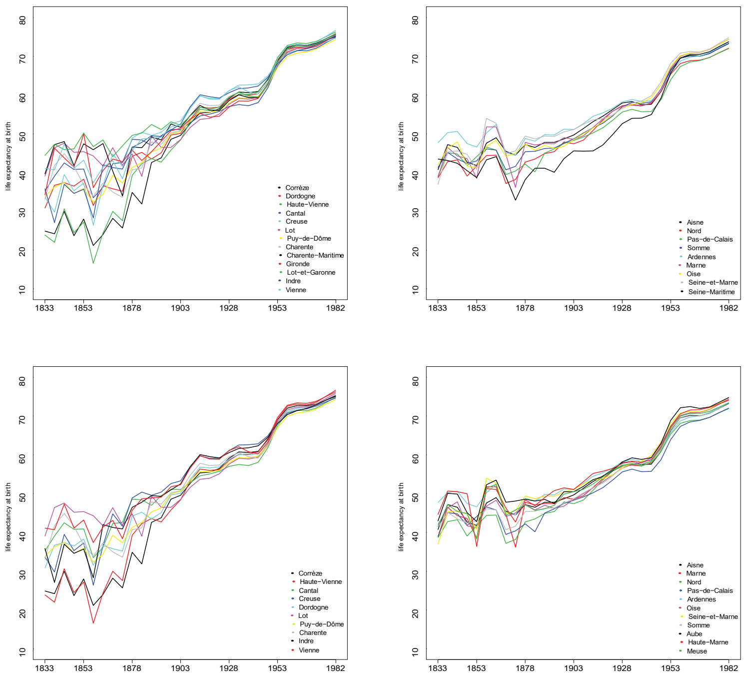


Fig. 5 Evolution of e_0 in the high (H-H) and low (L-L) clusters obtained using Euclidean (upper) and Manhattan (lower) distances.

In these graphs we can observe that, as was the case in Figure 2, the start of the 20th century marked a change in the behavior of e_0 and consequently of d_{e_0}. The reason for this change is perhaps to be found in the epidemiological transition theory proposed by Omran (1998). In the period of receding pandemics of the 19th century, one might expect a different spatial clustering of the longevity revolution. Thus, we have subdivided our data-series into two subseries, until 1903 and after 1903, which we have analyzed separately in order to detect clusters, just as we have done with the full data set.

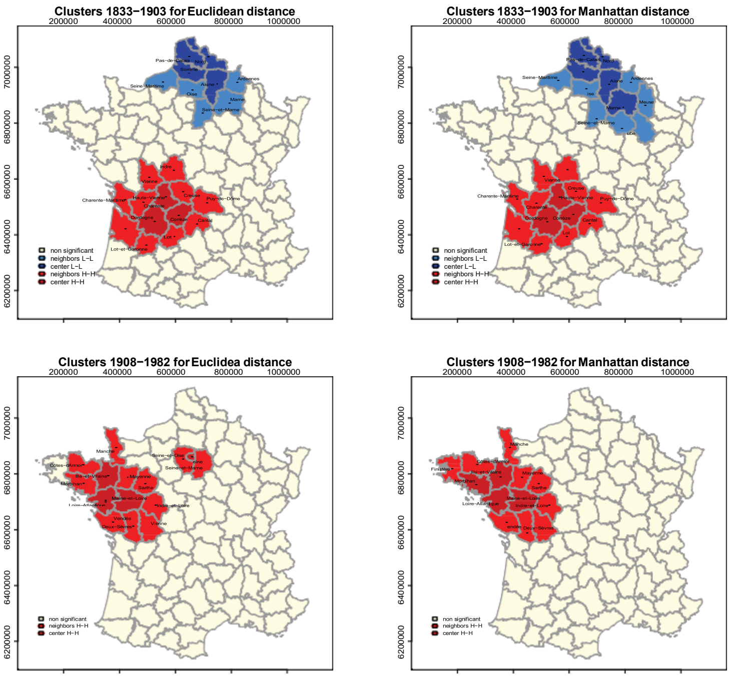


Fig. 6 Clusters of *départements* for the distances associated with e_0 for the periods 1833-1903 (upper) and 1908-1982 (lower).

The result can be observed in Figure 6. We can see that the clusters for the period 1833-1903 are very similar to those in Figure 4, which would confirm that it is the greater variability of e_0 during this period that predominates in the formation of clusters. In the 20th century period there are no clusters of the L-L type, and only H-H clusters appear, which are very different from all the earlier ones. If we observe the values of d_{e_0} in the centers and the means in the neighbors of these clusters, $\overline{d}_{e_0}$, shown in Tables 16 and 17 in Appendix 1, we will see that they are much lower than those of the clusters H-H obtained using all the data (Tables 12 and 13). This striking difference explains why the clusters from the 20th century are eclipsed when all the data are analyzed together, and again brings out the lower variability of e_0 during this period.

4.2 Spatial regression

Table 3 shows a summary of the regression of distance associated with e_0, d_{e_0}, with respect to the distances associated with the other three variables, d_{If}, d_{Ig} and d_{Im}, for the OLS model. Following Elhorst (2014), we take the OLS model as point of departure and we test whether the spatial lag model or the spatial error model is more appropriate to describe the data using the classic Lagrange Multiplier (LM) test (Anselin, 1988; Florax and Yoon, 1996). Table 4 contains the results of the LM tests for both distances. These results support the use of spatial models (3) and (4) as the LM tests are significant.

Table 3 Result for the OLS model

	Euclidean distance		Manhattan distance	
variable	β	p-value	β	p-value
constant	8.399	0.0103	27.928	0.0189
d_{If}	78.455	0.0002	76.353	2.36E-05
d_{Ig}	-19.984	0.0156	-19.898	0.0058
d_{Im}	27.428	0.0098	25.791	0.0021
log-lik	-283.159		-400.125	

Table 4 Lagrange Multiplier test for the OLS model

	Euclidean distance			Manhattan distance		
test	statistics	p-value	df	statistics	p-value	df
lag	19.6903	9.11E-06	1	16.0449	6.19E-05	1
error	26.6879	2.39E-07	1	25.0383	5.62E-07	1

Table 5 shows a summary of the spatial regression of d_{e_0}, over the three distances associated with the variables, d_{If}, d_{Ig} and d_{Im}. There is hardly any difference between the coefficients of the independent variables in the same model for both distances, and the most notable difference is that of the constants, which can be explained by the different size of the two distances. In any case, the constants of the models with spatial effects are not significantly different from zero. The distance d_{Ig} has a negative effect on d_{e_0} in all the models, which can be explained if we look at the graphs in Figure 2, which clearly show how e_0 and I_g go in opposite direction over time. The same holds for e_0 and I_f but less markedly, this is perhaps the reason why its effect on e_0 is positive. We would like to emphasize the impact of neighboring *départements*, having both, ρ and λ, values of around 0.6 in all four models, it means that the value of d_{e_0} or ε, in one *département*, increases around increases around 60% of the mean of the values in its surrounding areas. Finally, if we consider the value of the *loglikelihood*, the models based on the Euclidean distance perform better, and between them the spatial error model is slightly better.

Table 5 Result for spatial models

model	variable	Euclidean distance β	p-value	Manhattan distance β	p-value
spatial lag	constant	-2.578	0.3677	-11.468	0.2889
	d_{If}	65.644	0.0002	63.714	2.45E-05
	d_{Ig}	-16.914	0.0132	-17.795	0.0032
	d_{Im}	25.501	0.0040	24.537	0.0005
	ρ	0.590	8.02E-06	0.561	3.49E-05
	log-lik	-273.156		-391.560	
spatial error	constant	4.488	0.2205	13.243	0.3280
	d_{If}	86.122	9.52E-05	80.652	7.84E-06
	d_{Ig}	-18.567	0.0258	-18.373	0.0093
	d_{Im}	35.798	0.0005	33.652	1.87E-05
	λ	0.655	3.66E-07	0.664	4.30E-07
	log-lik	-270.189		-387.347	

Table 6 enables us to perceive the extent to which the inclusion of the spatial covariable in the OLS model is effective. The table shows the values of the Moran index obtained from the residuals of the two spatial models. Both models eliminate spatial self-correction to a level of $\alpha = 0.001$, although the spatial error model shows better performances, as can be deduced from its Moran index and log-likelihood. This holds for the models obtained with both distances.

Table 6 Moran index for residuals of spatial models

model	Euclidean distance I de Moran	p-value	Manhattan distance I de Moran	p-value
lag	0.1173	0.0274	0.1437	0.0101
error	0.0462	0.1956	0.0584	0.1484

4.3 Model diagnostics

Given their definition, it is to be expected that the three indices we used are correlated, which will affect the distances derived from them and might give rise to problems of multicollinearity in the OLS model. These correlations are $r_{d_{If},d_{Ig}} = 0.6303$, $r_{d_{If},d_{Im}} = 0.2748$, and $r_{d_{Ig},d_{Im}} = 0.6406$. To test for the presence of multicollinearity in the model, we obtained the variance inflation factor (VIF) for each variable. The values are shown in Table 7.

The interpretation of the size of these VIF's, that is, whether or not they are large, is the subject of a specific commentary on page 376 of the classic book by Draper and Smith (1998). These authors write: *"Obviously, how large a VIF value has to be to be large enough comes back to the question of when*

Table 7 VIF values for the variables in OLS model

distance	d_{If}	d_{Ig}	d_{Im}
Euclidean	1.3193	1.6521	1.3340
Manhattan	1.3594	1.7229	1.3636

an R^2 is large enough and perhaps should be thought on in that manner. In some writings, specific numerical guidelines for VIF values are seen, but they are essentially arbitrary. Each person must decide for himself or herself". Nonetheless, there is a certain consensus when 10 is established as the maximum threshold (O'brien, 2007) and about the need to eliminate correlated variables from the model (O'brien, 2016). As a result, and given the values in Table 7, we can accept that our model does not display multicollinearity in spite of the correlations that we have mentioned. It is therefore not necessary to eliminate any of the variables.

The Breusch-Pagan (B-P) test of heteroscedasticity and the Kolmogorov-Smirnov (K-S) test for normality applied to the residuals of the three models are shown in Table 8. Normality is accepted in the spatial models but not in the OLS for the Manhattan distance. The residuals of the three models present heteroscedasticity.

Table 8 Heteroscedasticity and normality test for the three models

		Euclidean distance			Manhattan distance		
	model	statistic	p-value	df	statistic	p-value	df
B-P test	OLS	14.447	0.002	3	10.810	0.013	3
	lag	16.704	0.001	3	15.505	0.001	3
	error	18.384	0.000	3	20.519	0.000	3
K-S test	OLS	0.088	0.091		0.121	0.003	
	lag	0.090	0.074		0.101	0.027	
	error	0.085	0.122		0.088	0.093	

The Q-Q plots of the residuals of the three models for both distances are shown in Figure 7 and help us to understand the heteroscedasticity of the models. In all these, the residual in the top right-hand corner is a striking feature: this corresponds to the *département* of Seine, the capital of which is Paris.

The anomalous behavior of the *département* of Seine is explained if we look at Figure 8, which shows the different behavior over time of its e_0 with respect to its neighbors, especially until the end of the 19th century. As a result of this, it has the largest values of d_{e_0} , while the values for the distances based on the three indices do not occupy extreme positions. All of these values are shown in Table 9.

Fig. 7 Q-Q plot for the residuals of the three models for Euclidean (upper) and Manhattan (lower) distances

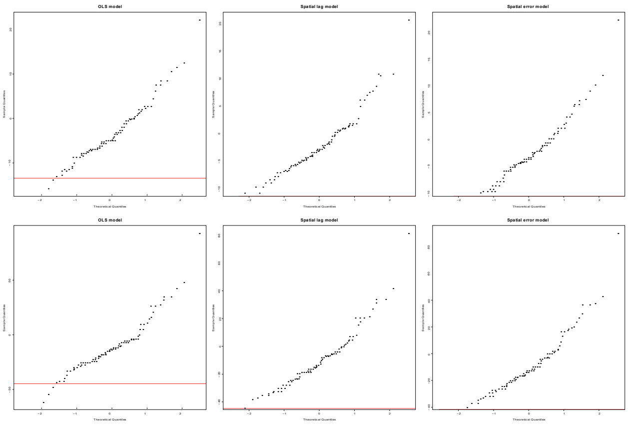


Fig. 8 Evolution of e_0 in Seine *département* and its neighborhood

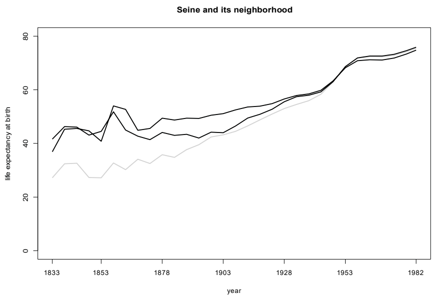


Table 9 Distances for Seine *département*

	Euclidean distance				Manhattan distance			
	d_{e_0}	d_{lf}	d_{lg}	d_{lm}	d_{e_0}	d_{lf}	d_{lg}	d_{lm}
Seine	50.6765	0.1657	0.2820	0.4568	206.8207	0.6947	1.2247	2.1905

4.4 Direct and indirect impacts for the spatial autoregressive model

The parameters of the ordinary least square and the spatial error models in Tables 3 and 5 offer a straightforward, direct interpretation. Each of them represents the variation in the variable response if the independent variable associated with the parameter increases by one unit when the others stay the same.

LeSage and Pace (2009) propose an alternative matrix expression for the spatial lag model of equation (3),

$$y = (I_n - \rho W)^{-1}(\beta_0 \iota_n + X\beta + \varepsilon), \tag{5}$$

where y represents the n observations of the dependent variable, I_n the unit matrix of dimension n, ι_n the unit vector of dimension n, X the matrix of the n observations of each of the p independent variables, β the vector of parameters, ρ the spatial coefficient and W the matrix of neighborhood (LeSage and Pace, 2009). This expression shows that any variation in an independent variable in one of the *départements* directly affects the effect of the dependent variable on that *département*, but also indirectly affects its neighbors and their neighbors, and in a kind of boomerang effect, ends up by affecting the original *département* itself. The size of the direct and indirect impacts depends, in accord with equation (5), on the matrix of neighborhood W, the spatial coefficient, ρ, and the coefficient β of the variable in the model. This means that the same variation of one variable in different *départements* has different effects. For this reason, the authors cited above propose measures that represent the mean of the effects produced by one variable when it varies the same way in all the *départements*. The details are to be found in the above cited text (LeSage and Pace, 2009).

These mean effects, for the spatial lag model in Table 5, are shown in Table 10, which also shows the p-valor for testing that these impacts are null. All of these are significant at $\alpha = 0.05$ except the indirect effects of d_{lg} and d_{lm} for the Euclidean distance and d_{lg} for the Manhattan distance. The significance of the coefficients mainly confirms the direct and indirect impact between the similarity of behavior over time of the life expectancy at birth and the overall fertility index. However, for the other two measures, only the direct impact is confirmed in both distances.

We can observe that the direct effects do not differ much from the β associated with each variable in the spatial lag model. This should not surprise us, as the direct effects are nothing other than the corrections of the former owing to the spatial effect introduced in the model. The differences that we can observe are due to the feedback of the indirect effects suffered by the other *départements*. This is a kind of round-trip phenomenon which eventually comes into equilibrium.

Table 10 Mean impacts for the spatial lag model

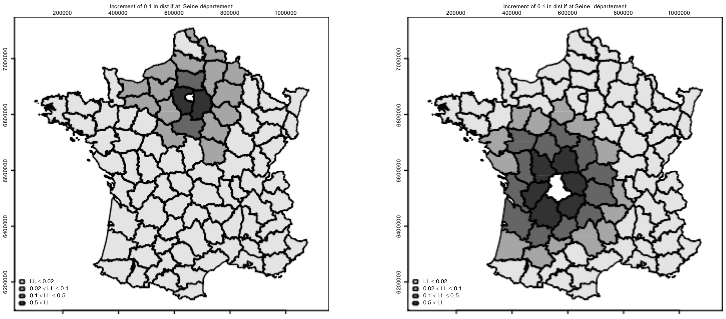
		direct	p-value	indirect	p-value	total	p-value
Euclidean	d_{lf}	72.6594	0.0001	87.2591	0.0442	159.9185	0.0039
	d_{lg}	-18.7211	0.0122	-22.4828	0.1276	-41.2038	0.0462
	d_{lm}	28.2265	0.0035	33.8982	0.0780	62.1247	0.0193
Manhattan	d_{lf}	69.6740	0.0000	75.4971	0.0322	145.1711	0.0015
	d_{lg}	-19.4599	0.0035	-21.0863	0.0725	-40.5461	0.0169
	d_{lm}	26.8325	0.0005	29.0751	0.0408	55.9076	0.0047

It is sometimes interesting to study the effect of the changes in one variable in a particular area on the response variable in the region itself, and in the other regions. As an example, let us consider what happened when the *départements* of Seine and Haute-Vienne had an increase of 0.1 in the variable d_{lf} for the Manhattan distance. Table 11 shows the direct and indirect effects of both increases and confirms the comment made above about how these effects vary from one *département* to another. Figure 9 allows us to see how the effects are cushioned as we move further away from the origin of the change.

Table 11 Impacts for Seine et Haut-Vienne

	Direct	Indirect
Seine	6.7338	2.5086
Haute-Vienne	6.8547	7.9359

Fig. 9 Indirect impacts due to an increment of 0.1 in d_{lf} at Seine (left) and Haut-Vienne (right) *départements*.



5 Conclusions

The definition of new variables based on the life expectancy at birth and fertility index has enabled us to summarize the evolution over time of the geographical differences in demographic behavior. These new variables measure similarities in the way trends evolved between the *départements* and their neighbors.

Changes in life expectancy at birth in the French *départements*, measured using the associated distance, show a clear spatial autocorrelation, as we can see from the maps in Figure 3 and the Moran indices shown in Table 2. The LISA values reveal two significant clusters with different signs, with scarcely any differences between the two distances (see Figure 4). One of these, the H-H cluster, is located in the west-central of the country and, if we recall how the distances were obtained, means that these *départements* followed very different evolution over time. The L-L cluster, situated in the north of the country, consists of *départements* with a similar evolution over time. We also indicate that when the data postdating 1903 are analyzed separately, this gives rise to new H-H clusters which differ from those that occurred before (see Figure 6 and Tables 16 and 17), characterized by smaller distances between the nucleus and the neighbors than those found in the earlier clusters. Both types of cluster were predictable on the basis of Figure 3 with the spatial distribution d_{e_0} in the French *départements*. This clearly shows two reas in the north and mid-west of the country that correspond to these two clusters.

Our exploratory analysis enabled us to identify two significant clusters which point to two sets of *départements*, and our regression models confirmed the relations between the new variables. The first cluster is represented by *départements* that are very different from each other, with major differences in life expectancy at birth alongside large differences in their overall fertility index and nuptiality index but only small differences in their marital fertility index. This area therefore reflects French *départements* which differ in terms of life expectancy, fertility and nuptiality but which are similar in terms of fertility within marriage. These are very heterogeneous groups of *départements* situated in the Eastern area, with the Dordogne in the center, and including some neighboring *départements*.

The second cluster consists of French *départements* which are similar to each other, with minor differences in life expectancy at birth and small differences in the overall fertility index and nuptiality index but large differences in the marital fertility index. Unlike the other group of *départements*, in this category we find the French *départements* which have similar life expectancy, fertility and marriage rates, but which differ in terms of fertility within marriage. This is a highly homogeneous group of *départements* situated in the north, with Pas-de-Calais in the center.

Both clusters are formed through a contagion effect resulting from historical factors and other variables related to geographical and socio-economic conditions which affect the inhabitants of these areas who share the same lifestyle and surroundings. According to Barbieri (2013), who analyzes the geographical variability within mortality in France over the period 1976-2008, cardiovascular diseases make the largest contribution and account for one-third of the variability between *départements* for all ages, even though cancer is the main cause of death for France as a whole. Moreover, the *départements* in the north are characterized by a lower life expectancy than the others, whose relative mortality for advanced ages is high (60-79 years). None the less, the departements in the mid-west generally have a higher life expectancy and higher relative mortality among people aged under 30. Although levels of poverty and income inequality are indeed high in northern France, the relationship between the economic situation and mortality in French *départements* is a complex one (Barbieri, 2013) which needs further investigation.

Use of spatial regression models is justified by the auto-correlation that exists between the residuals in the OLS model, confirmed by the LM tests. The coefficients of the three covariables are significant. The positive coefficients of

d_{If} and d_{Im} in both models mean that when one *département* becomes more distant from its neighbors in the trends in If and Im, its e_0 also follows suit. The negative value of the coefficient associated with d_{Ig} means that this has the opposite effect.

One further issue of particular interest warrants discussion here, which is the question of the spatial model to be used. In our case, the choice would seem to be doubtful, because although the best model, if we look at the significance and log likelihood, is that of spatial error, the nature of the phenomenon itself should be taken into account as a criterion to choose the model. This is no a trivial issue, and has been a matter of concern for experts in the field such as LeSage and Pace (2009) and Ward and Gleditsch (2008). An interesting discussion about which of the two spatial models is most appropriate to describe the spatial dependence of a variable can be found in Sparks and Sparks (2010).

Returning to our discussion in Section 4.1 about information loss resulting from summarizing the time series using one of the distances defined in that section for each variable, it must be pointed out that the results obtained are interesting, but the dynamics of the process is lost. It suffices to glance again at the graphs in Figure 5 to see that relevant information about this dynamic cannot be reflected accurately in a spatial study such as this. These graphs show a process of increasing uniformity of e_0 that starts at the beginning of the 20th century, with much greater variability in the 19th century. Our research focus could be widened to include the study of the variable *time*, either through spatial panel models which enable us to incorporate the action of covariables, or through a study similar to the present article with distances weighted by a kernel centered on year t_0, whose weights would mitigate the effect of values that are distant in time, in which t_0 could be varied over the time frame of the study.

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Appendix 1

Summary of H-H clusters

Table 12 H-H clusters and neighbors for Euclidean distance

center	Corrze	Dordogne	Haute-Vienne
neighbors	Cantal Creuse Dordogne Lot Puy-de-Dme Haute-Vienne	Charente Charente-Maritime Corrze Gironde Lot Lot-et-Garonne Haute-Vienne	Charente Corrze Creuse Dordogne Indre Vienne
d_{e_0} center	38.66	28.46	36.11
$\bar{d}_{e_0}$ neighbors	26.91	28.45	26.28

Table 13 H-H clusters and neighbors for Manhattan distance

center	Corrze	Haute-Vienne
neighbors	Cantal Creuse Dordogne Lot Puy-de-Dme Haute-Vienne	Charente Corrze Creuse Dordogne Indre Vienne
d_{e_0} center	147.89	141.30
$\bar{d}_{e_0}$ neighbors	106.33	101.80

Summary of L-L clusters

Table 14 L-L clusters and neighbors for Euclidean distance

center	Aisne	Nord	Pas-de-Calais	Somme
neighbors	Ardennes Marne Nord Oise Seine-et-Marne Somme	Aisne Pas-de-Calais Somme	Nord Somme	Aisne Nord Oise Pas-de-Calais Seine-Maritime
$\bar{d}_{e0}$ center	11.23	11.42	9.40	11.58
$\bar{d}_{e0}$ neighbors	14.22	10.70	11.51	14.40

Table 15 L-L clusters and neighbors for Manhattan distance

center	Aisne	Marne	Nord	Pas-de-Calais
neighbors	Ardennes Marne Nord Oise Seine-et-Marne Somme	Aisne Ardennes Aube Haute-Marne Meuse Seine-et-Marne	Aisne Pas-de-Calais Somme	Nord Somme
$\bar{d}_{e0}$ center	46.20	52.89	50.70	42.64
$\bar{d}_{e0}$ neighbors 59.12	61.01	47.1	51.08	

Summary of H-H clusters for data subsets

Table 16 H-H clusters and neighbors for the period 1908-1982 for Euclidean distance

center	Ille-et-Vilaine	Loire-Atlantique	Maine-et-Loire	Seine
neighbors	Ctes-d'Armor Loire-Atlantique Maine-et-Loire Manche Mayenne Morbihan	Ille-et-Vilaine Maine-et-Loire Morbihan Vende	Ille-et-Vilaine Indre-et-Loire Loire-Atlantique Mayenne Sarthe Deux-Svres Vende Vienne	Seine-et-Marne Seine-et-Oise
$\underline{d}_{e_0}$ center	9.00	9.75	8.74	10.13
$\bar{d}_{e_0}$ neighbors	6.81	7.59	7.14	7.53

Table 17 H-H clusters and neighbors for the period 1908-1982 for Manhattan distance

center	Ille-et-Vilaine	Loire-Atlantique	Maine-et-Loire	Morbihan
neighbors	Ctes-d'Armor Loire-Atlantique Maine-et-Loire Manche Mayenne Morbihan	Ille-et-Vilaine Maine-et-Loire Morbihan Vende	Ille-et-Vilaine Indre-et-Loire Loire-Atlantique Mayenne Sarthe Deux-Svres Vende Vienne	Ctes-d'Armor Finistre Ille-et-Vilaine Loire-Atlantique
$\underline{d}_{e_0}$ center	31.50	35.49	30.71	23.82
$\bar{d}_{e_0}$ neighbors	23.58	26.74	24.39	26.73