The spatial convergence of population aging in southern Europe

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Abstract

Population aging challenges the fiscal balances of a state, the role of the elderly and young people in society, the renewal of the labor market, resource allocation, etc. Populations age at different rates so that some regions are catching up with others, while others continue to widen the gap. The concept of convergence can be applied to demographic indicators, including aging.

This paper aims to study the spatial dimension of the convergence of population aging. We decided to use Markov chains to analyse the spatial convergence of southern Europe (Portugal, Spain, France, Italy) from 1998 to 2013.

Keywords

Spatial convergence, Population aging, Spatial Markov chain, Southwestern Europe, Spatial model

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Introduction

Neoclassical economic theories hypothesize that poor countries have stronger growth rates than rich countries. Therefore, this differential in growth rate implies that poor countries are catching up to rich countries (Solow, 1956). Econometricians developed many statistical methods to measure the convergence of economic growth.

If the economy is at the origin of the concept of convergence, it is nevertheless possible to adapt it to other social sciences. Demographics lends itself rather well to the exercise: convergence is at the heart of the demographic transition (Wilson, 2001). All global populations are seeing their fertility and mortality decrease, so there should be a convergence of fertility and life expectancy. Groups experiencing their demographic transition later are also those who will live it most quickly. The decline in fertility throughout the world is a good example. The fertility of late transition countries will certainly catch up with countries whose transition is complete or almost complete. In this case, there may be a phenomenon of convergence, as not all populations have the same rate of demographic transition.

Spatial convergence of aging populations?

Population aging is a consequence of the demographic transition. The declining birth rate causes a narrowing of the base of the age pyramid. The decline in mortality induces aging in the population only when progress on death concerns those of advanced age. In this case, the top of the age pyramid grows.

Almost all post-transitional populations share a low fertility rate, a low mortality rate, and therefore an aging

population. This is all the more aggravated if fertility stagnates over a prolonged period below the replacement birth rate level. The differences in the degree of aging come from the various rhythms of demographic transition.
Most demographic phenomena, which include aging, are particularly interesting to the geographer, since they show, more or less, a strong spatial autocorrelation (Decroly, Grasland, 1992). Spatial clustering of fertility, mortality or migration rates value can often be seen. The components of population aging are often spatially autocorrelated. It is easy to imagine a spatial convergence of aging for a population. As territories do not all age at the same rate(under the effect of fertility, mortality, migration and structures inherited by age)they may converge with neighbouring territories. It is this phenomenon that we seek to measure.

Data for Southern Europe

We study the spatial convergence of aging territories in southern Europe (France, Spain, Italy and Portugal) using NUTS3 level. Data were collected on national statistics offices sites. Population aging is measured as the percentage of those 65 or more in a population. We measured it for each year between 1998 and 2013.

Method #1: the interest of Markov chains

The first measures of convergence were initiated in Econometrics (Barro, Sala-i-Martin, 1992). These were primarily a regression (β-convergence) and a test of statistical dispersion (σ-convergence). Besides the fact that the β-convergence suffers from Galton's problem (Friedman, 1992), these methods are used to test whether there is an overall convergence in a statistical sample, but do not inform about the dynamics of the statistical distribution of the study variable and can hide the existence of multiple convergence clubs (Quah, 1996). Therefore they are widely criticized. Recently, these two methods have been adapted for local use (Yildirim *et al.*, 2009; Bourdin, 2013).

Another way to study local convergence is to use Markov chains (Quah, 1996). We follow this approach here. Specifically, we consider a discrete indicator of the phenomenon of interest, observed on successive dates on a set of individuals. In our study, the discrete indicator is the proportion of those 65 or more. It is assumed that this indicator takes a finite number of values, called "states". The Markov chain approach considers that the value of the indicator at a given date for a given individual depends only on its value on the date immediately before. The distribution of the indicator at a given date then is entirely determined by the probabilities of passing from one state to another between two successive dates in the past. The probabilities for a given period are usually formed into a transition matrix. If we assume that these transition matrices are identical in all periods, the chain is said to be homogeneous. The estimate of the transition matrix from the data leads to an estimate of the distribution of the indicator at each moment, as well as its long-term distribution, called ergodic distribution. This distribution is particularly interesting to get a picture of the distribution if the transition probabilities are infinitely repeated.

This method is particularly interesting for a study on convergence. Indeed, it is possible to measure the convergence of young populations to old populations and *vice versa*. It also shows whether the ergodic distribution is unimodal or multimodal. In the first case, the transition probabilities indicate that in the long term, individuals converge on a single point. In the second case, it would imply several points of convergence, revealing the existence of convergence clubs (Durlauf, 1996).

Method #2: the interest of spatial Markov chains

In applying the above methodology to our data, we do not take into account the spatial dimension of convergence. One way around the problem is to standardize our data using the average of neighboring territories (Le Gallo, 2004). In this way, the value indicates the difference in aging between a territory and its neighbors. We apply a Markov chain model to these standardized data to study the spatial convergence. This method allows us to highlight local convergences: to locate the territories that are catching up to their neighbors (or the opposite).

The previous method only allows the measurement of the convergence or divergence of trajectories of aging between a territory and its neighbors. However, it does not measure the absolute age of a territory, i.e. its position at each instant in the distribution of aging. To overcome this problem, one solution is to use probabilities of different transitions according to the state of its neighbors (Rey, 2001). In such a model, the transition matrix provides information on the probability of an area to move from one state to another, according to the state of its neighbors: this is the spatial Markov chain. In this case, we standardize our data using the mean of the proportion of people aged 65 or more of the year

For these new measures, a neighborhood matrix based on a 1st order queen contiguity is used in order to calculate, for every individual, the mean value of its neighbors.

Method #3: spatial Markov chains with continuous states space

So far, since the states of the Markov chains are discrete, we must cut out the variable studied (proportion aged 65 or more) in classes. The results are thus dependent on the constitution of the state, i.e. the selected division. One way to overcome this weakness is to use Markov chains with continuous state space. Thus, we do not consider a finite number of states, but a continuum of values. We thus are evaluating not a transition matrix but the densities of conditional probabilities.
The representation of non-spatial Markov chains with continuous states is possible using a 3-dimensional graph, with the status of individuals at time t-1 on the x-axis (*x*), the status of individuals at time t on the y-axis (*y*), and the density on the z-axis (Figure 1).

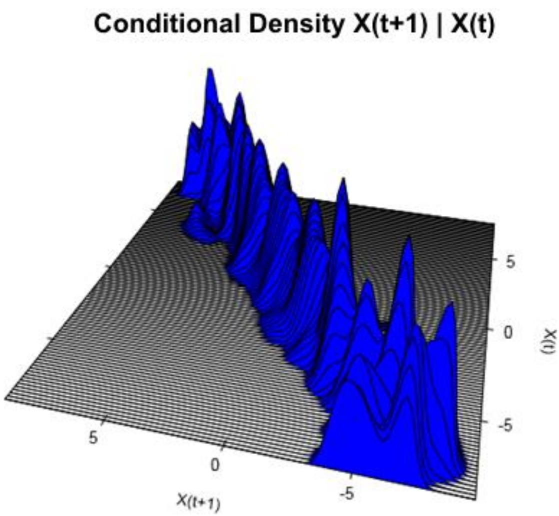

Figure 1 - 3D graphic of conditional density, with standardized data according to year

Representing spatial Markov chains in continuous states remains quite difficult, because a fourth dimension of the state of neighbors (*v*) must be added. This new dimension must be discrete to be combined with the 3 previous ones.

$$f_t(y|X_t = x, V = v) = \frac{f_t(x,y,v)}{f_t(x,v)}$$

To enhance the graphics reading, we choose to represent the conditional densities on a 2D graph, according to the neighborhood classes, where high densities are black and low densities are white. (Figure 2) The results become finer, allowing further analysis. The same neighborhood, according to the value of the territory at time *t*, can produce together a greater probability of convergence (red zone) and of divergence (blue zone).

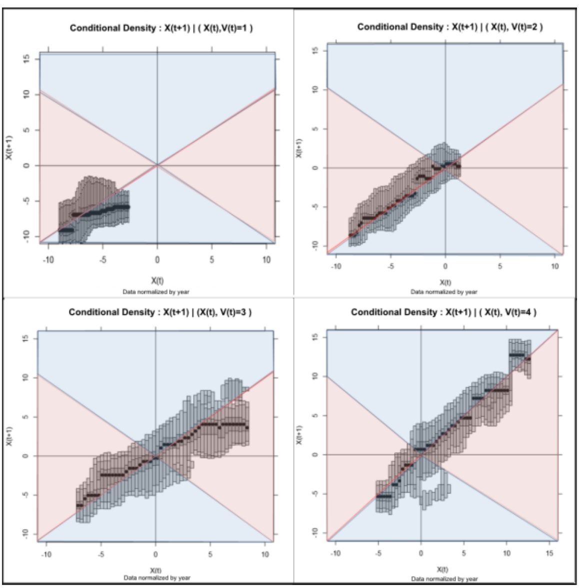

Figure 2 - 2D graphic of conditional densities according to the neighborhood, with standardized data according to the yearly mean.

Conclusion

The modelling of ageing in Southern Europe using spatial Markov chains with continuous states space allowed us to overcome the inherent problem to discrete spatial Markov chain, i.e. the oversimplification of discrete data. Now, to go beyond the simple reading of graphics, it will be necessary to develop objective indexes.

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