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A SPATIO-TEMPORAL ANALYSIS OF MIGRATION RATES IN THE EMILIA-ROMAGNA REGION

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1. INTRODUCTION

Migration, i.e. the movement of people from one location to another on any geographic scale, affects both the origin and the destination areas. When the rate of natural increase is low, as in developed countries, an increasing share of population change may be attributed to migration (Eurostat, 2009). Migration is usually regarded as domestic (or internal) migration when the movement of people within national boundaries is involved, and as international migration when it refers to movement across those boundaries (Franklin, 2003).

Migration is a major factor in demographic redistribution, and at the international level it is one of the three most important flows, together with flows of goods and services (commodities), and flows of capital (OECD, 2009).

Several studies examining the determinants of migration have emphasized not only economic factors, but also "quality of life" factors (Cebula, 1979; Cebula and Payne, 2005; Cebula and Alexander, 2006). Those factors encouraging people to migrate have been extensively analysed, but it is still unresolved the question about why migrants decide to move to one particular country rather than to another (Hooghe *et al.*, 2008).

The aim of the present analysis is to understand how net municipal migration rates are influenced by the demographic structure. The analysis focuses on the 341 municipalities within the Emilia-Romagna Region of Italy.

The present study is set out as follows: section 2 introduces the phenomenon of migration in the Emilia-Romagna Region; section 3 presents the statistical model adopted to describe migration flows; section 4 discusses the results of our estimations while the final section offers a brief discussion to our findings.

2. MIGRATION IN THE EMILIA-ROMAGNA REGION: DATA AND CONCEPTS

In the period from 1970 to 1991, the population of the Emilia-Romagna Region remained substantially stationary, and internal migration was not sufficient to balance the negative natural increase rate. Since the 1970s, the absolute number of elderly has continued to rise, while mortality rates have been falling faster than the Italian average (Rettaroli *et al.*, 2009). Because of the relationship between this mortality trend and the total fertility rate that has been below the replacement level since 1968, Emilia-Romagna now has one of the oldest populations in Europe.

From the mid-1990s onwards, there have been an increasing number of international migration flows towards Italy. In the Emilia-Romagna Region, these flows have given rise to a new and unexpected period of population growth, which has contributed towards slowing the aforesaid ageing process.

During the same period, internal flows have slowed, although they still determine one of the highest internal migration rates among Italian regions.

International and, to a lower extent, internal migration, have resulted in an average annual regional growth rate of about 1% from 2002 to the present day. The annual rate of population increase reached 1.5% both in 2003-2004, as a result of the regularization of foreign migrants, and in 2007-2008 following the enlargement of the European Union.

Migrants tend to be either young or middle-aged, and apart from their direct contribution to population growth, they also make a positive contribution to the annual birth rate, thus, limiting the negative effect of the natural balance on annual population growth. In 2008, 80% of international migrants were below the age of 40, and the number of births from foreign parents accounted for 20.7% of total annual births.

Internal migrants tended to be younger than average for the Emilia-Romagna Region population as a whole, but older than their international counterparts (Regione Emilia-Romagna, 2007).

Net migration flows to the Emilia-Romagna Region are characterised by a strong degree of heterogeneity among municipalities which prove attractive to both Italian and foreign migrants for different reasons.

Within this context, our aim is to investigate whether net migration rates at the municipal level are influenced by the age structure of the population. Our specific aim is to assess how the ageing index (percentage of people aged 65 and over), the economically active population index and the child-women ratio (number of children aged less than five per childbearing-aged woman), influence migration into and out of the regional boundaries.

The last indicator is a proxy measure of the level of fertility, and is more stable than the total fertility rate (TFR) in municipalities with small populations. Moreover, it is also an indicator of a municipality's past migration history. If a municipality has traditionally attracted young families and women coming from areas with high fertility, then this indicator will be high. On the other hand, if a municipality has gradually lost these segments of the population, then the same indicator will display low values.

The index accounting for the age structure of the economically active population was chosen under the hypothesis that an ageing labour force could result in the inability to replace those persons retiring from gainful employment in the presence of an unchanging productive structure. Thus, municipalities showing high values of the economically active population index can attract new, younger workers.

The attractiveness of an area may be influenced by the ageing index as well, since elderly people require personal support and care, and such services are frequently provided by migrant women.

Between 70% and 80% of the total annual migration balance is accounted for by the foreign population, and thus we want to analyze the total migration rate by separating the contribution made by flows of foreigners and flows of Italians. This will enable us to assess differences in the spatial distribution of the two components, and to ascertain whether the relationship to the set of chosen covariates is the same for both foreign and Italian migrants.

Data relating to migratory inflows and outflows, population size and demographic structure indicators at a municipal level, are collected by the Italian National Institute of Statistics (ISTAT), and are available at the website www.istat.it.

Statistical modelling of migration flows needs to take spatial association into account. In fact, the migratory process, involving population movement from one area to another, has in itself a spatial component; while migration flows are connected to the size and structure of contiguous areas' populations. Thus, an analysis of the mere in-migration and out-migration rates (the ratio of migrants to the average population) is not enough, given that such rates do not make any adjustments for the proximity of a given area to other areas with different amounts of population (Fotheringham *et al.*, 2000; Rogers *et al.*, 2002; Voss, 2007). Congdon (2010) claimed that nearby areas contribute towards establishing the 'migration context' of a particular region, "namely the size and proximity of nearby areas with populations at risk of migrating to that area, or offering potential destinations for out-migrants from that area". Models with a non-spatial specification do not adjust for such structural effects, and may provide an incomplete picture of the phenomenon.

The spatio-temporal analysis is conducted at municipal level, moreover, within a hierarchical setting also temporal trend at provincial level is monitored.

3. STATISTICAL MODELLING OF NET MIGRATION RATES

In this section we describe two hierarchical models that can be used for the spatio-temporal modelling of migration flows. Hierarchical models are an effective tool for building complex models from relatively simple sub-models. The Bayesian framework is the most suitable for managing this kind of model (Wikle *et al.*, 1998). Within the context of the space-time modelling of migrations, a certain complexity arises because temporal dependence, spatial dependence and the interaction between space and time have to be modelled simultaneously, together with dependence on other explanatory variables such as structural demographic covariates.

Let y_{kti} and z_{kti} denote respectively counts of in and out migratory flows at year t, $t=1,...,T$, in municipality i, $i=1,...,N$. The subscript k, $k=1,2$ indexes Italian and foreign migrants respectively.

The area-specific net migration rate at time t for subgroup k, can be directly estimated from the data as the difference between in and out migratory rates:

$$\hat{\mu}_{kti} = \frac{y_{kti}}{P_{ti}} - \frac{z_{kti}}{P_{ti}} = \mathrm{R}^I_{kti} - \mathrm{R}^O_{kti}$$

Where P_{ti} denotes the average population in year t and in municipality i and superscripts I and O refer respectively to incoming and outcoming flows.

Quantities R^I_{kti} and R^O_{kti} are the maximum likelihood estimates under the Poisson likelihood. There are two main drawbacks associated with the maximum likelihood estimators, particularly when small areas are included in the analysis[1], namely:

- overdispersion (unstructured heterogeneity): variations in the counts exceed what would be expected from Poisson inference, i.e. the areas display heterogeneity with regard to the levels of migration;
- Poisson-based inference fails to take account of spatial patterns in the data (structured heterogeneity, spatial variations).

In what follows, two models are proposed for the analysis of migration flows. Both models include covariates for modelling the dependence of migration flows on the demographic structural indicators described in section 2. Moreover, the models include province-specific intercepts modelled as a random walk process in order to encompass the structure of the temporal dependence characterising the dynamics of migration flows. In order to model the province-specific migration rate, a dummy variable $\mathbf{D}_i$, i=1,...,n, is introduced into the models, so that $D_{ij}=1$ if the *i-th* area belongs to the *j-th* province, and $D_{ij}=0$ otherwise, j=1,...,9. Model 1 is a non-spatial model, while model 2 explicitly takes account of spatial correlation by introducing spatial random effects. For both models, the likelihood function for incoming and outgoing flows in the municipalities in question is specified as a Poisson distribution:

$$y_{kti} \left| r^I_{kti} \sim Poisson(r^I_{kti} P_{ti}) \qquad k=1,2;\ t=1,...,T;\ i=1,...,N \right.$$

$$z_{kti} \left| r^O_{kti} \sim Poisson(r^O_{kti} P_{ti}) \right.$$

Migration flows are modelled as conditionally independent given the migration rates r^I_{kti} and r^O_{kti}. The models differ at the second level of the hierarchy.

[1] In 2008, 45% of the 341 municipalities considered here had 5,000 or fewer inhabitants.

Model I

In and out migration rates are modelled as follows:

$$\log(r^I_{kti}) = \mathbf{D}'_i \boldsymbol{\alpha}^I_{kt} + \mathbf{X}'_{ti}\boldsymbol{\beta}^I_k + \varepsilon^I_{kti}$$
$$\log(r^O_{kti}) = \mathbf{D}'_i \boldsymbol{\alpha}^O_{kt} + \mathbf{X}'_{ti}\boldsymbol{\beta}^O_k + \varepsilon^O_{kti}$$

Here, $\boldsymbol{\alpha}^I_{kt} = (\alpha^I_{kt1}, \alpha^I_{kt2}, ..., \alpha^I_{kt9})$ are province-specific intercepts designed to represent province-specific temporal dynamics. For each province, intercepts follow a random walk process, i.e.:

$$\alpha^I_{ktj} \sim N(\alpha^I_{k(t-1)j}, \sigma^I_{\alpha kj}) \qquad j = 1,...,9$$

This represents a first-order smoothing non-stationary temporal model (see West and Harrison, 1997) which can be interpreted as a limiting form of the autoregressive first-order model, and is non-stationary. In the Bayesian framework, a normal prior distribution is usually assumed for the starting points of the random walk processes α^I_{k0j}.

Terms ε^I_{kti} and ε^O_{kti} are unstructured random effects designed to model the extra-Poisson variation (i.e. overdispersion) characterising the observed data, and are modelled as follows:

$$\varepsilon^I_{kti} \sim N(0, \sigma^I_{\varepsilon kt}) \qquad \varepsilon^O_{kti} \sim N(0, \sigma^O_{\varepsilon kt})$$

The role of these random effects is to shrink the observed migration rates toward the regional mean. This shrinkage effect is more pronounced for areas with low population size, and thus more exposed to random variability, while maximum likelihood estimates for areas with large population size are preserved. The shrinkage effect enables us to obtain posterior estimates characterised by lower uncertainty compared to the maximum likelihood estimates.

The hierarchy of the model is completed in a Bayesian framework by hyperprior specification. Diffuse Normal independent priors $N(0,1000)$ are assumed for each component of the coefficient vectors $\boldsymbol{\beta}^I_k$ and $\boldsymbol{\beta}^O_k$. Independent small parameters inverse Gamma distributions ($InvGamma(.001,.001)$) have been specified for the variance parameters $\sigma^I_{\varepsilon k}$, $\sigma^O_{\varepsilon k}$, $\sigma^I_{\alpha kj}$.

Model II

In this model, spatial random effects are introduced and the migration rates are modelled as:

$$\log(r^I_{kti}) = \mathbf{D}'\boldsymbol{\alpha}^I_{kt} + \mathbf{X}'_{ti}\boldsymbol{\beta}^I_k + \varphi^I_{kti} + \upsilon^I_{kti}$$
$$\log(r^O_{kti}) = \mathbf{D}'\boldsymbol{\alpha}^O_{kt} + \mathbf{X}'_{ti}\boldsymbol{\beta}^O_k + \varphi^O_{kti} + \upsilon^O_{kti}$$

where dependence on the covariates is the same as specified in Model I. Moreover, terms υ_{kti}^{I} and υ_{kti}^{O} represent spatially unstructured random effects with the same role of terms ε_{kti}^{I} and ε_{kti}^{O} in Model I, while random effects φ_{kti}^{I} and φ_{kti}^{I} are designed to represent spatial variation.

Within the context of areal data modelling, spatial dependence is managed by specifying a suitable joint distribution for the elements of $\boldsymbol{\varphi}_{kt}$: one commonly-used model in such cases is the Conditional AutoRegressive (CAR) model, a Markov Random Field (Mardia, 1988) in which dependence is limited to the neighbouring areas, that is, the conditional distribution of the variable in a given area is independent of the variable in non-neighbouring areas. Thus, to specify a CAR model, a neighbouring structure has to be selected. Various neighbouring structures have been proposed in the literature. In this paper, following the most popular approach, we consider areas as neighbours if they share a boundary. Information about the neighbouring structure is summarized in the adjacency matrix $\mathbf{W}$, with entries $w_{ij} = 1$ if areas *i* and *j* share a common boundary, or $w_{ij} = 0$ otherwise. The full conditional distributions for the spatial random effects are specified as follows:

$$\varphi_{kti} \mid \varphi_{ktj}, j \sim i, \tau_{\phi kt}^{I} \sim N\left(\sum_{i=1}^{N} w_{ij}\varphi_{ktj}, \frac{\sigma_{\varphi kt}^{I}}{m_i} \right)$$

where m_i is the number of neighbours of the $i-th$ area, and $\sigma_{\varphi kt}^{I}$ is the variance parameter scaled, for each area, by the number of its neighbours. Thus, the conditional variance is inversely proportional to the spatial information. This conditional specification gives rise to the well-known Intrinsic CAR (ICAR) joint distribution, a multivariate Normal distribution denoted as:

$$\boldsymbol{\varphi}_{kt}^{I} \sim CAR(\sigma_{\varphi kt}^{I})$$

This distribution is improper and a sum-to-zero constraint on the spatial random effects is needed in order to ensure identifiability. The proposed model represents an adaptation of the well-known Besag, York and Mollié model (Besag *et al.*, 1991), widely used for areal data modelling, to spatio-temporal modelling of migration rates. The inclusion of spatial random effects allows shrinkage of the migration rates toward the local mean, and offers a compromise between local shrinkage and the global shrinkage generated by unstructured random effects.

As regards hyperprior specification, we follow the same approach undertaken for Model I, and we assume small parameters inverse gamma distribution for the variance parameter of the ICAR distributions $\sigma_{\varphi kt}^{I}$.

As regards inference, we adopt a fully Bayesian approach. The net migration rate posterior distribution can be obtained as:

$$p(\mu_{kti} \mid y_{kti}, z_{kti}) = p(r^I_{kti} - r^O_{kti} \mid y_{kti}, z_{kti})$$

and a point estimate can be obtained by summarising the posterior distribution via posterior expectation, giving $\tilde{\mu}_{kti} = E(\mu_{kti} \mid y_{kti}, z_{kti})$. This estimator has the advantage that it takes account of overdispersion and spatial correlation, while the direct estimator $\hat{\mu}_{kti}$ fails to take account of these features.

Posterior distributions are not obtainable in an analytical form because of the complexity of the distributions involved in the hierarchical model. Posterior summaries of model parameters are computed by means of Monte Carlo Markov Chain (MCMC) routines, as they are implemented in the OpenBUGS software (Spiegelhalter *et al.*, 1998).

Model performances are compared via Deviance Information Criterion (DIC) (Spiegelhalter *et al.*, 2002). DIC is a model selection criterion according to which the model performance is evaluated as the sum of a measure of fit, the posterior mean of the deviance $\bar{D} = E[-2\log(lik(data \mid parameters))]$, and a measure of complexity, the effective number of parameters p_D, obtained as the difference between the deviance posterior mean and the deviance evaluated at the parameters posterior mean. Thus $DIC = \bar{D} + p_D$: a model is selected if it shows a lower DIC value.

4. RESULTS

Models I and II are estimated by means of MCMC sampling. Inference is based on 10,000 samples from the MCMC algorithm, after 15,000 burn-in iterations have been conducted for each model. Convergence has been checked by means of the visual inspection of the trace plots of sample values versus iteration, and of the autocorrelation plot in each chain. A comparison in terms of DIC shows that Model 2 has to be preferred, i.e. spatial correlation needs to be taken into account.

TABLE 1

Model comparison: DIC

	Model I				Model II			
	$\bar{D}$	$\hat{D}$	*DIC*	p_D	$\bar{D}$	$\hat{D}$	*DIC*	p_D
Y	43491	41136	48468	2355	41420	36690	46160	4736
Z	40352	37982	45056	2370	38430	33950	42910	4478
Total	83843	79118	93524	4725	79850	70640	89070	9214

This is confirmed by testing for residuals' spatial correlation: such test (not shown) highlights residuals' spatial correlation for model I, while the null hypothesis of spatial independence is not rejected for model II. In what follows the results obtained using model II are summarised.

TABLE 2

Estimated regression coefficients and 95% credibility intervals

		In migration flows				Out migration flows		
		Posterior Mean	95% Posterior C.I.			Posterior Mean	95% Posterior C.I.	
Italians	β^I_{11}	0.104	-0.328	0.641	β^O_{11}	0.363	0.018	0.838
	β^I_{12}	-0.809	-1.036	-0.561	β^O_{12}	-0.494	-0.766	-0.307
	β^I_{13}	0.735	0.612	0.892	β^O_{13}	0.421	0.313	0.57
foreigners	β^I_{21}	0.812	0.249	1.355	β^O_{21}	1.712	0.923	2.515
	β^I_{22}	-1.679	-2.029	-1.423	β^O_{22}	-1.668	-2.004	-1.291
	β^I_{23}	0.129	0.003	0.258	β^O_{23}	0.853	0.681	1.041

Estimated coefficients and 95% credibility intervals for in- and out- migration rates are reported in Table 2. The first subscript equals 1 for Italians and 2 for foreigners, while the second one refers, respectively, to the ageing index, the economically active population structure index and the child-women ratio.

A positive effect of the ageing index is found for both inflow and outflow of Italians and foreigners, with a stronger effect for the latter. This relationship could be linked on the one hand to the increasing positive contribution of elderly to the overall movement, and on the other hand to the direct link between care for the elderly and in-migration flows.

Municipalities with an ageing economically active population show, all other factors being equal, low immigration and emigration rates, the effect being stronger for foreigners than for Italians. When this index displays high values, the group with the greatest propensity to move (those aged 15-39) is underrepresented, and the total population tends to generate low outflows, which may explain the estimated effect for emigration. The 'compression' effect for immigration flows is unexpected, and could be due to an uncontrolled variable related to labour market structure.

The child-women ratio induces positive variations in immigration. Given the youthful age of immigrants, this relationship could express the propensity of young migrant families to reside where other families with children, maybe migrants, reside. The child-women ratio is rising in those municipalities characterised by a high proportion of migrants. Migrant women, particularly if foreign, make an appreciable contribution to the number of births in most of the municipalities.

The hierarchical structure of the estimated model allows estimation of province-specific net migration rate, after covariates-adjustment. The province-specific temporal trend is shown in Figure 1, where estimated net migration rates in the period 2002-2008 along with credibility intervals refer to the provinces of Reggio Emilia and Bologna. These provinces are representative of the trend observed in all the provinces of the region.

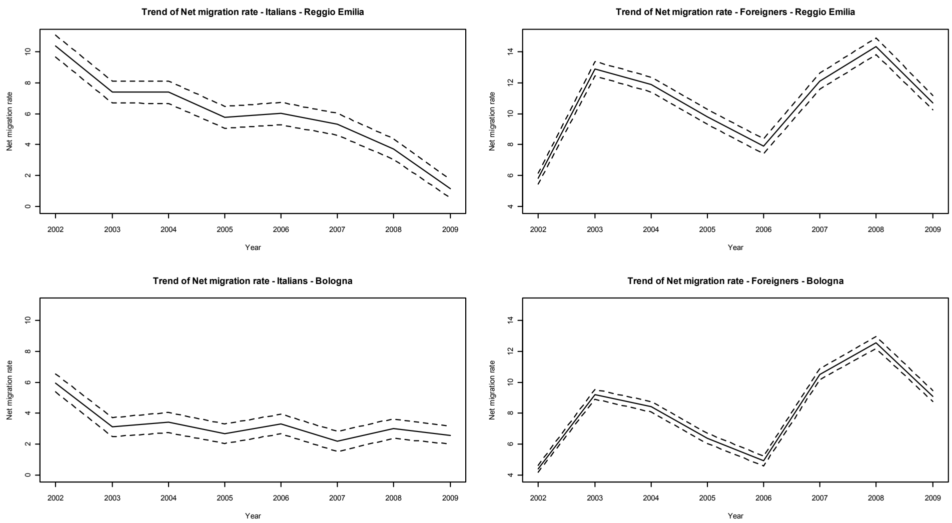

Figure 1 – Temporal trend of the net migration rate and 95% confidence bands for Italians and foreigners in the provinces of Reggio Emilia and Bologna.

The evolution of the net migration rate involving foreigners has been strongly affected by the national regularization of immigrant workers in 2002, with visible effects witnessed in 2003 and 2004, and by the 2007 enlargement of the European Union to include Romania and Bulgaria. The net migration rate of foreigners is constantly higher in the Reggio Emilia province than in the Bologna province. The shape of the estimated trend is common to all provinces.

The net migration rate of Italians has displayed a different trend: while in the Reggio Emilia province the rate is clearly decreasing, in the Bologna province it appears to be roughly stationary. All other provinces display a trend similar to that of Reggio Emilia, albeit with different levels of the rates.

In general, all the provinces display a higher average net migration rate for foreigners than for Italians.

Maps of municipality net migration rates are shown in Figures 2 and 3, for Italians and foreigners respectively. The two maps, reporting estimates for 2009, use the same cuts-off point to define interval limits in order to facilitate comparison. The contribution of foreigners to population growth is clearly higher than that of Italians migrants. Italians' net migration rate is also negative in many municipalities, meaning that the Italian population in those areas is falling, whilst the foreign population is on the increase.

Temporal trends for municipalities show that when the population exceeds 20,000 inhabitants, the net migration rate for Italians tends to be negative, while the contribution of foreigners tends to be highly significant. New influxes of foreigners tend to be concentrated in municipalities with a relatively large population. Italians tend to prefer moving from large cities to relatively small municipalities, whereas their net migration towards towns is either negative or null.

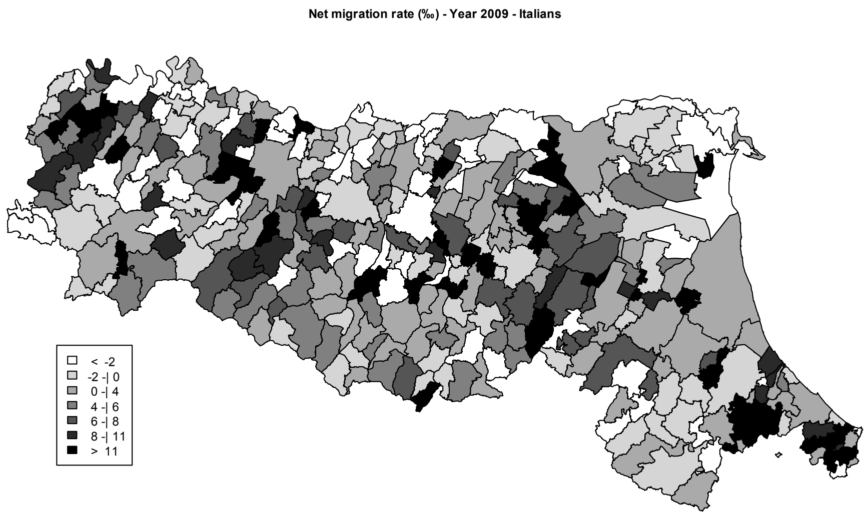

Figure 2 – Spatial distribution of the net migration rate (Italians) in 2009.

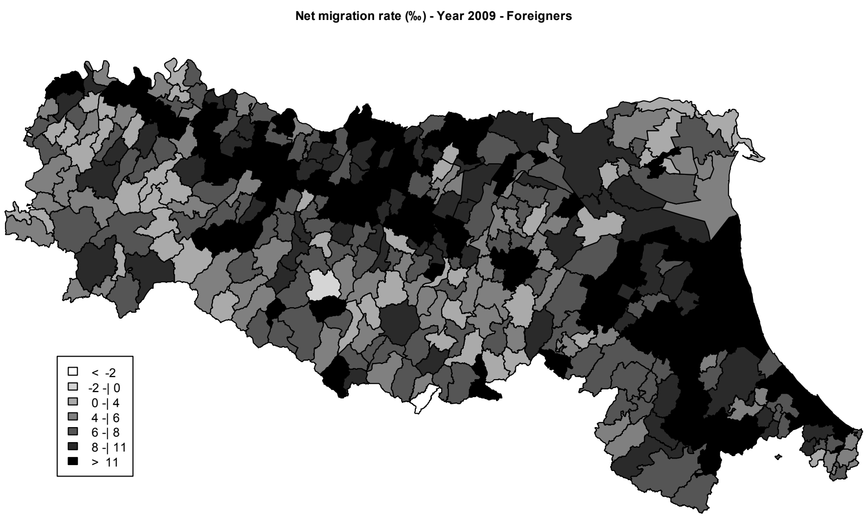

Figure 3 – Spatial distribution of the net migration rate (Foreigners) in 2009.

5. CONCLUSIONS AND FURTHER DEVELOPMENTS

Migration is a global phenomenon encompassing two distinct issues: migrants leave their neighbouring for some reason while they choose the place they decide to live in for other reasons. Economic, cultural and social factors have been widely explored as the factors encouraging or forcing people to migrate, but the reasons why they choose certain areas rather than others, despite the similarities between them, remain largely unexplored.

Municipality migration flows may be influenced by the presence of nearby areas with populations at risk of migrating, or offering potential destinations for outgoing migrants. The spatial correlation of the net municipality rates has to be taken into account in order to get a better understanding of the phenomena in question.

Migrant flows are distinguished from citizenship in an attempt to discover different spatial distributions of foreign and Italian migrants. The maps of municipality migration rates reveal that these two components of the population make very different contributions to total population growth, and tend to be located differently.

Our analysis has identified the existence of spatial dependence in the net municipality migration rates, and has treated it, within the framework of areal data modelling, by specifying a CAR model.

Provincial trends during the period 2002-2009 are very similar, since flows of foreigners have been affected by national legislation and are at a higher level during that period than the equivalent flows of Italian migrants. The contribution of internal flows basically follows two different patterns, either decreasing or stationary, with the latter being the case in the province of Bologna only.

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REFERENCES

J. BESAG, J. YORK, A. MOLLIÈ, (1991), *Bayesian image restoration, with two applications in spatial statistics*, "Annals of the Institute Statistical Mathematics", 43, pp. 1-21.

R. J. CEBULA, (1979),*The Determinants of Human Migration*, Lexington, MA: Lexington Books.

R. J. CEBULA , J. E. PAYNE, (2005), *Net migration, economic opportunity and the quality of life, 1999-2000*, "International Review of Economics and Business", 52(2), pp. 245-254.

R. J. CEBULA, G. M. ALEXANDER, (2006), *Determinants of net interstate migration, 2000-2004*, "The Journal of Regional Analysis and Policy", 36(2), pp. 116-123.

P. CONGDON, (2010), *Random-effects models for migration attractivity and retentivity: a bayesian methodology*, "Journal of the Royal Statistical Society", Series A, 173, part 4, pp. 755-774.

A. FOTHERINGHAM, T. CHAMPION, C. WYMER, M. COOMBES, (2000), *Measuring destination attractivity: a migration example*, "International Journal of Population Geography", 6, pp. 391-422.

R. S. FRANKLIN, (2003), *Domestic migration across regions, division and states: 1995 to 2000*, Census 2000 Special Reports, CENSR-7, Population Division , U.S. Census Bureau.

M. HOOGHE, A. TRAPPERS, B. MEULEMAN, T. REESKENS, (2008), "International Migration Review", 42 (2), pp. 476-504.

EUROSTAT, (2009), *Regional Yearbook 2009*.

K. V. MARDIA, (1988), *Multi-dimensional multivariate Gaussian Markov random fields with application to image processing.* "Journal of Multivariate Analysis", 24, pp. 265-284.

OECD, (2009), *International Migration Outlook: SOPEMI 2009.*

REGIONE EMILIA-ROMAGNA, Servizio controllo strategico e statistica (a cura di) (2007), *Quadro demografico dell'Emilia-Romagna al 1/1/2007*, Bologna, Clueb.

R. RETTAROLI, G. ROLI, A. SAMOGGIA, (2009), *Evolution of survival at old ages during the 20th century in Emilia Romagna*, "Statistica", anno LXIX (1).

A. ROGERS, F. WILLEKENS, J. LITTLE, J. RAYMER, (2002), *Describing migration spatial structure*, "Papers in Regional Science", 81, pp. 29-48.

D. J. SPIEGELHALTER, N. BEST, B. P. CARLIN, A. VAN DER LINDE, (2002), *Bayesian measures of model complexity and fit (with discussion)*, "Journal of the Royal Statistical Society", Series B, 64, pp. 583-639.

D. SPIEGELHALTER, A. THOMAS , N. BEST, (1998), *WinBugs: Bayesian inference using Gibbs sampler, Manual Version 1.2.* Imperial College, London and Medical Research Council Biostatistics Unit, Cambridge.

P. V. VOSS, (2007), *Demography as a spatial social science,* "Population research and policy review", 26, pp. 457-476.

M. WEST, J. HARRISON, (1997), *Bayesian forecasting and dynamic linear models*, Springer-Verlag, New York.

C. K. WIKLE, L. M. BERLINER, N. CRESSIE, (1998), *Hierarchical Bayesian space-time models*, "Environmental and Ecological Statistics", 5, pp. 117-154.

SUMMARY

A spatio-temporal analysis of migration rates in the Emilia-Romagna Region

Migration – the movement of people from one location to another on any geographic scale – affects both the areas of origin and of destination. The aim of the present analysis is to understand how municipalities' net migration rates are influenced by the demographic structure of the population. The analysis is conducted on the 341 municipalities within the Emilia-Romagna Region of Italy, by means of a spatio-temporal Bayesian hierarchical model. The need to take account for spatial dependence is demonstrated by comparing a spatial and a non-spatial model. Model hierarchy enables us to highlight province-specific temporal trends for both Italian and foreign flows: a decreasing trend is evident for Italians, while an increasing trend is observed for foreigners. At a spatial level, we show that the contribution of foreigners to population growth is higher than that of Italians migrants. Italian net migration rates are also negative in many municipalities that are losing their Italian population and increasing the number of foreigners residing there.