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## Spatial Analysis of Urban Growth in Spain (1900-2001)

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## **SPATIAL ANALYSIS OF URBAN GROWTH IN SPAIN (1900-2001)**

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### **ABSTRACT**

The purpose of this paper is to improve the knowledge of the Spanish urban system. We study the evolution of population growth among the group of 722 municipalities included in the Spanish urban areas over the period from 1900-2001. Urban population cross-sectional distribution is characterized by means of nonparametric estimations of density functions, and the growth process is modeled as a first-order stationary Markov chain. A spatial SUR model is also estimated for the Zipf's law. Spatial effects are then introduced within the Markov chain framework using regional conditioning and spatial Markov chains.

**Key words:** Convergence, urban growth, spatial autocorrelation, spatial SUR models, spatial Markov chains.

JEL Classification: **C14, C21, O18**

## 1. INTRODUCTION

The purpose of this paper is to improve the knowledge of the Spanish urban system. The urbanization process has mainly taken place during the 20th century producing significant processes of industrialization and economic growth. Specifically in Spain, this process has not been uniform and it produces different results depending on the definition of “urban area”. In fact, there is no official definition of “urban area” in Spain and it is not easy to obtain statistical data at the level of municipalities. Hence, the analysis of the Spanish urban system is still scarce. Nevertheless, some authors have considered the group of “main cities” –above 50,000 inhabitants- as urban units (e.g. Lanaspá *et al.*, 2003, 2004, Mella and Chasco, 2006).

In this paper, we propose to work with the set of municipalities that forms the Spanish “urban areas”, as defined by the *Ministerio de Fomento* (2000). It is a heterogeneous municipality group that not only includes the main cities but also all the satellite towns that conforms the complete metropolitan area. We study the evolution of population growth among this set of 722 municipalities included in the present Spanish urban areas over the period from 1900-2001. Urban population cross-sectional distribution is analyzed by means of nonparametric estimations of density functions and the growth process is modeled as a first-order stationary Markov chain. The evolution of the shape of the population cross-sectional distribution and the changes in the municipalities’ relative positions within this distribution show the existence of alternate divergence/convergence trends.

The article is organized as follows. In the first section, the evolution of the disparities between the Spanish urban municipalities is characterized by examining the population cross-sectional distribution over the period from 1900 to 2001. For that purpose, we use nonparametric estimation of density functions, the growth process is modeled as a stationary first-order Markov chain, and mobility indices are computed. In the second section, we explicitly consider the spatial dimension within the Markov chain framework using spatial Markov chains (Rey 2001). This tool allows studying how geographical environment can explain the population growth of an urban municipality. It also measures the extent to which this environment influences the urban municipalities’ relative position within the population cross-sectional distribution. The article concludes with a summary of key findings.

## 2. THE EVOLUTION OF SPANISH URBAN SYSTEM 1900-2001

This section examines growth in the Spanish urban system, changes in the relative size distribution of urban municipalities, and mobility of these nuclei through the distribution, over a 100-year period.

### 2.1. Data

To explore these issues, we want to construct a data set with urban areas defined consistently over the century. For that purpose, we have considered the classification proposed by the *Ministerio de Fomento* (2000). It divides the Spanish territory into urban areas, which include a set of 722 municipalities: 1) a set of 495 towns included in the 65 “Large Urban Areas” (areas above 50,000 inhabitants each); 2) the group of 227 municipalities considered as “Small Urban Areas” (towns above 10,000 inhabitants not included in the Large Urban Areas, with minor corrections). This is rather different from the approach in Lanaspá *et al.* (2003), who operated with a sample of 100 largest cities<sup>1</sup> as proxies of the Spanish urban system.

On its side, the sample of 722 urban municipalities comprises the set of towns considered as “urban areas” by the Spanish Ministry of Urbanism and Public Works (*Ministerio de Fomento*, 2000)<sup>2</sup>. These urban settlements are also located across the whole Spanish territory: Andalusia (137), Aragón (10), Asturias (25), Balearics (13), Canary Islands (29), Cantabria (5), Castille and León (23), Castille-La Mancha (17), Catalonia (192), Valencian Community (96), Extremadura (11), Galicia (32), Madrid (33), Murcia (19), Navarre (18), Bask Country (58), Rioja (2), Ceuta and Melilla.

The evolution of population distribution is analyzed using the Census data over the period from 1900 to 2001. The data on per capita GDP are extracted from the Spanish Office for Statistics (INE) databank<sup>3</sup>.

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<sup>1</sup> These authors chose a relatively arbitrary number of “largest cities” after finding that the results were qualitatively robust to different sample sizes. In a posterior paper, Lanaspá *et al.* (2004) chose different subsets with the 100, 300, 500 and 700 most-populated municipalities.

<sup>2</sup> The Ministry of Urbanism and Public Works divides the Spanish territory into urban areas, which include a set of 722 municipalities: 1) a set of 495 towns included in the 65 “Large Urban Areas” (areas above 50,000 inhabitants each); 2) the group of 227 municipalities considered as “Small Urban Areas” (towns above 10,000 inhabitants not included in the Large Urban Areas, with minor corrections).

<sup>3</sup> This data are available in the INE webpage: <http://www.ine.es>

## 2.2. The evolution of the shape of urban population distribution

The evolution of the shape of urban size may be detected by estimating the non-parametric kernel density estimates of the urban set population distribution and by analyzing its monomodality or multimodality characteristics. We examine relative urban municipality size distribution in 1900 and the way this distribution has changed over time in 1950, 1970 until 2001. Figure 1 shows the relative log urban municipality size distributions in 1900, 1950, 1970 and 2001. This density plot may be interpreted as the continuous equivalent of a histogram in which the number of intervals has been set to infinity and then to the continuum. From the definition of the data, 1 on the horizontal axis indicates Spanish average city size, 2 indicates twice this average, and so on.

**Figure 1** Densities of log relative urban municipality size

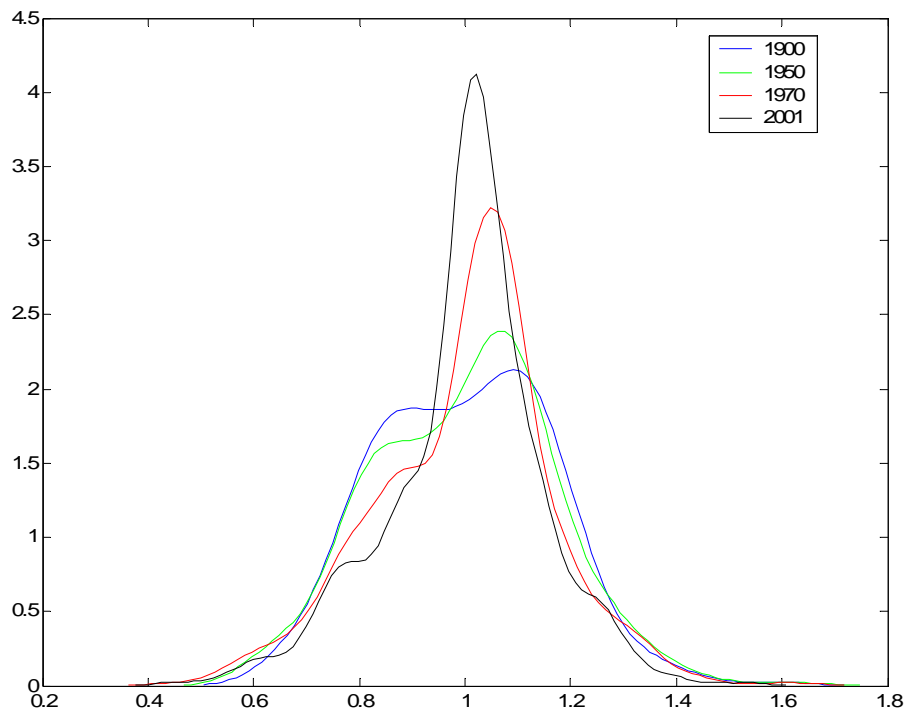


Figure 1 plots an interesting graph where the distribution is bimodal in 1900 and goes to a unimodal distribution in 2001 (minor mode around 70-80%). This may reflect the existence, in 1900, of a group of urban municipalities with sizes below the average, converging toward a lower population level than the rest of the towns. Compared with 1900, more urban municipalities reported in 2001 population are about the Spanish average. The

distributions in 1900 and 1950 are quite similar, while the central mass significantly increased in the 1970 to reach the highest point in 2001 distribution. This progressive concentration of probability mass around 100% can be interpreted as an evidence for slight convergence. This result is similar to others in the literature (Lanaspa *et al.*, 2003, 2004, for Spanish largest cities; Anderson and Ge, 2005, for Chinese cities), though differs from the Black and Henderson (2003) results for US metropolitan areas.

### **2.3. The Zipf's law, or the rank-size rule**

We begin our exploration of the evolution of the Spanish urban municipality size distribution by using Zipf's law, or the rank-size rule. Zipf (1949) claimed that the size distribution of cities follows a Pareto law (Pareto, 1897), or can be described by a potential law, when it holds that:

$$R = a \cdot S^{-b} \tag{1}$$

where,  $R$  is the city rank order of the population distribution;  $S$  is the population of the cities; and  $a$  and  $b$  are parameters, with the latter being the Pareto exponent, always positive by construction.

The rank size rule, which emerged from regularly observed features of the data lacking any economic theoretic foundation, has recently been analyzed especially by Gabaix and Ioannides (2004); as well as Rossi-Hansberg and Wright (2004), Cordoba (2003), Ioannides and Overman (2003), Dobkins and Ioannides (2000), Overman and Ioannides (2001), Gabaix (1999), Eaton and Eckstein (1997), Krugman (1996), between others.

The size distribution of cities is more or less equal, depending on the value of the Pareto exponent ( $b$ ). At the limit, if  $b$  tends to infinity, then all the cities will be of an equal size. When  $b$  is equal to one, we obtain the well-known rank-size rule or Zipf's law. The Pareto exponent can be interpreted as a convergence indicator. In effect, values that fall over time indicate relatively more important roles (increasing weight) for the largest cities and, therefore, a divergence trend inside the group of urban municipalities or greater metropolitan concentration. By contrast, increasing values represent a convergence dynamics, or in other words, greater dispersion of the population outside the large metropolitan areas and a more balanced population distribution between urban centers of different sizes.

Empirically, departing from equation (1), we take logarithms on both sides and estimate the resulting linear expression for the set of 722 urban municipalities ( $i$ ) for each decade ( $t$ ):

$$\ln R_{it} = \ln a_t - b_t \cdot \ln S_{it} + \varepsilon_{it} \quad (2)$$

We have followed the strategy suggested by Anselin (1988, pp. 203) for the specification of spatial SUR models. In a first stage, we have estimated Equation (2) by Ordinary Least Squares (OLS) for the 11 spatial equations individually considered. For each model, we have tested the presence of spatial effects as well as the non-diagonality of the inter-equation covariance matrix (temporal correlation)<sup>4</sup>. As shown in Table 1, the OLS errors of the 11 equations are non-normal and exhibit heteroskedasticity and spatial autocorrelation (as pointed out by Jarque-Bera, Koenker-Basset and Kelejian-Robinson tests, respectively). Therefore, we can conclude that both spatial effects are present in the 11 models. Regarding spatial autocorrelation, the non-normality of the errors does not allow using the Lagrange Multiplier (LM) tests. The Kelejian-Robinson –though highly significant- cannot orient towards a spatial lag or spatial error formulation.

In addition, we can also test for the existence of temporal correlation between the 11 equations. For this purpose, we estimate by maximum likelihood Equation (2) as a spatial SUR model. The computation of the LM and LIK diagonality tests of the error covariance matrix –as well as the Wald test on the homogeneity of the parameters across equations- points out the superiority of a SUR specification over 11 individual ones. On the other side, both LM tests on spatial dependence allow rejecting the null of no spatial autocorrelation. The higher value of the LM test on spatial-error dependence is an indication that the correct specification is a spatial SUR spatial-error model (3) –instead of a spatial lag one (4)- as it shows a better performance in terms of goodness of fit (higher LIK and lower AIC).

$$\ln R_{it} = \rho_t \cdot W (\ln R_{it}) + \ln a_t - b_t \cdot \ln S_{it} + \varepsilon_{it} \quad (3)$$

$$\ln R_{it} = \ln a_t - b_t \cdot \ln S_{it} + [I - \lambda_t \cdot W] \varepsilon_{it} \quad (4)$$

where  $W$  is a spatial weight matrix, such that each element,  $w_{ij}$ , is set equal to 1 if urban municipality  $i$  is at most 160 km far from urban municipality  $j$ . The role of the spatial weight

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<sup>4</sup> The spatial SUR model can be defined as  $Y_t = X_t \beta_t + \varepsilon_t$ , where  $Y_t$  and  $\varepsilon_t$  are  $N$  by 1 vectors, and  $X_t$  is a  $N$  by  $K_t$  matrix of explanatory variables. In this model, the error terms are correlated in time. This specification generates a covariance matrix  $\Omega$  for the error term:  $E[\varepsilon \varepsilon'] = \Omega = \Sigma \otimes I$ , being  $\Sigma = \{\sigma_{ts}\}$  a  $T$  by  $T$  matrix, and  $\otimes$  the Kronecker product.

matrix is to introduce the notion of a neighborhood set for each urban municipalities. Similar results have been obtained with other specifications<sup>5</sup>.

**Table 1 Rank-size regressions, Spanish urban municipalities 1900-2001**

	OLS Basic model			Spatial SUR model (ML)		Spatial SUR spatial- error model (ML)			Spatial SUR spatial lag model (ML)				
	$\hat{\alpha}$	$\hat{b}$	JB	KB	KR	$\hat{\alpha}$	$\hat{b}$	$\hat{\lambda}$	$\hat{\alpha}$	$\hat{b}$	$\hat{\rho}$		
1900	11.04	-0.66	728	116	188	10.66	-0.62	10.68	-0.62	0.16	10.43	-0.62	0.04
1910	11.06	-0.66	748	111	249	10.65	-0.61	10.67	-0.61	0.19	10.29	-0.60	0.05
1920	11.04	-0.65	794	100	287	10.59	-0.60	10.61	-0.60	0.19	10.18	-0.59	0.06
1930	11.05	-0.64	668	89	313	10.55	-0.58	10.56	-0.58	0.20	9.99	-0.57	0.08
1940	10.91	-0.62	757	85	418	10.40	-0.56	10.41	-0.56	0.22	9.85	-0.55	0.08
1950	10.82	-0.60	682	82	493	10.30	-0.54	10.32	-0.54	0.22	9.69	-0.53	0.09
1960	10.81	-0.59	616	62	540	10.30	-0.53	10.32	-0.53	0.23	9.66	-0.52	0.09
1970	10.78	-0.57	614	37	580	10.31	-0.52	10.32	-0.52	0.26	9.48	-0.50	0.12
1981	10.67	-0.54	721	31	509	10.21	-0.50	10.23	-0.50	0.27	9.25	-0.48	0.14
1991	10.90	-0.56	744	25	369	10.39	-0.51	10.41	-0.51	0.25	9.51	-0.49	0.13
2001	11.39	-0.60	837	13	237	10.83	-0.54	10.87	-0.55	0.30	9.81	-0.52	0.14

**Diagonality tests**

LM test:	30,274	-	-
LIK ratio:	22,531	2,928	2,849

**Wald homogeneity test**

b parameter:	687	616	513
spatial parameter:		21	45

**Spatial dependence**

LM-spatial-error:	217	-	-
LM-spatial lag:	81	-	-

**Goodness of fit**

LIK	-	6,833	6,778
AIC	-	26.34	48.36

*Notes:*  $\alpha = \ln a$ . \* Null-hypothesis rejection between 1%-5%. *OLS* indicates ordinary least squares estimation. *JB* is the Jarque-Bera non-normality test on the residuals. *KB* is the Koenker-Basset test for heteroskedasticity. *KR* is the Kelejian-Robinson test for spatial autocorrelation in the error term. *ML* is the Langrange multiplier tests on spatial autocorrelation in the error terms. *LIK* is the log-likelihood ratio test. *AIC* is the Akaike Information Criterion.

Figure 2 shows the evolution through time of these three estimations of the Pareto exponent. Though the OLS estimators for this parameter are always higher, they follow a similar evolution.

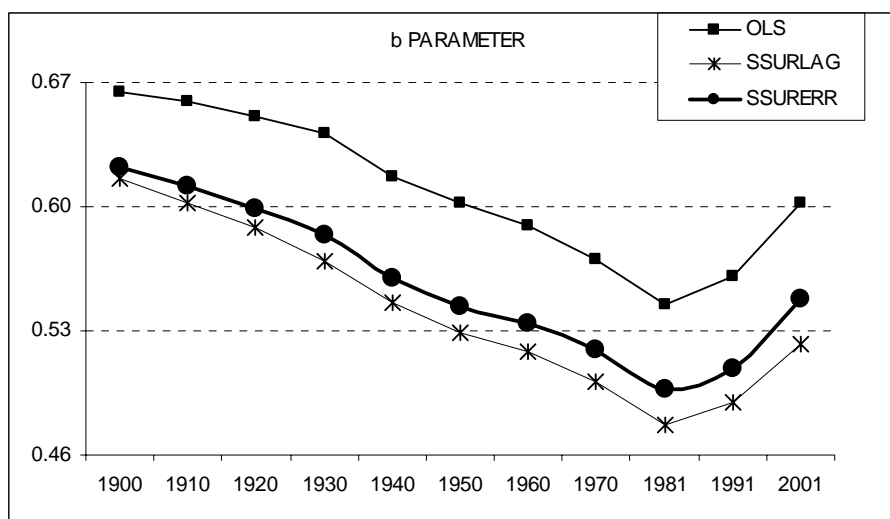
From Figure 2, it is clear that, in general terms, the estimation over time of the *b* parameter displays a decreasing trend until 1980, from which it starts to augment. As a result, we can deduce two different patterns of behavior over the course of the 20th century: from 1900 to 1980, the size distribution of the set of 722 urban municipalities is increasingly divergent whilst from the 1980s to the end of the period this distribution becomes growingly

<sup>5</sup> We have also used a contiguity spatial weight matrix using a Thiessen polygonalization of the Spanish territory for the 722 urban municipalities.



equal. Looking in depth, we can also distinguish two other sub-periods in the first moment: from 1900 to 1930 (smaller divergence) and 1930-1981 (steeped divergence). This result is more or less consistent with Lanaspá *et al.* (2003, 2004) that found the inflexion date in 1970 for the group of 100 Spanish largest cities, and 1981 for other sets of municipalities.

**Figure 2 Evolution of the estimations of the Pareto exponent (N=722)\***



\* **Note:** OLS is the OLS estimation; SSURLAG is the spatial SUR spatial lag model; SSURERR is the spatial SUR spatial-error model.

Consequently, the Zipf's law leads us to an interesting result –i.e., the existence of two main phases in the evolution of Spanish urban municipalities. The main one, which extends over 80 years, consists of a reduction of urban concentration only broken after the 80's. Inside the first stage, we can distinguish two sub-periods, in which the divergence course between urban municipalities has different speeds:

- From 1900 to the 30's, the  $b$  parameter shows a slower decreasing trend coinciding with a significant industrialization and urbanization expansion that led to progress and social changes in Spain. In the first decade, though most of the active population was located in the countryside, labor force began to migrate to the main industrial cities, e.g. Barcelona and Bilbao, as well as to Madrid and Valencia. Neutrality during the I World War and a capital stock growth (that came from the Americas and the international investment) helped the development of some industrial activities (located only in certain cities) that demanded more workers (Tuñón de Lara *et al.*, 1982). Moreover, during the 20's, industrialization and urbanization went on growing, especially in the Axis Madrid-North-Barcelona leading to an incipient development of

other satellite towns along the Cantabric Coast (Bilbao Estuary area, Santander, Asturian cities) and the Mediterranean Coast (Valencia and Alicante). However, during the mid 30's, the economic crisis and the Civil War stopped the urbanization process (Tuñón de Lara and Malerbe, 1982).

- From 1940 to the 70's, the  $b$  parameter experiments a quicker decline or in other words, during this period, the largest cities grew at significantly greater rates than the smallest population nuclei, exhibiting an intense divergent pattern of growth. In effect, during the 40's, Spain lived an autarkical regime that led to a real ruralization process: the main cities –destroyed after the Civil War- has to be re-built, hunger and poverty expelled a lot of people to the villages and, in general, urban population and active population decreased significantly. Nevertheless, some big cities grew a lot like Madrid (due to the huge centralization and burocratization of the Regimen), Barcelona and other capitals (Valencia, Saragossa, Alicante and Seville). The incipient political and economic openness lived during the 50's stopped the ruralization derive and put the basis for the decisive industrialization and tertiarization process lived during the 60's and 70's (Tuñón de Lara and Viñas, 1982). The industrial sector was severely constrained to be more competitive and lot of workers had to migrate to Europe or to the Spanish capitals and new economic centers. Development was geographically irregular and affected only the cities located in richer provinces: Guipúzcoa, Biscay, Barcelona, Navarre, Madrid and Álava. Nevertheless, the Development Plans also created new economic poles, such as Vigo, Pontevedra, Coruña and Ferrol (in Galicia), Valladolid and Burgos (in Castile), Huelva, Cádiz, Seville (in Andalusia), Saragossa (in Aragón) and Badajoz (in Extremadura). If in 1960 only the 30% of Spanish population lived in cities above 100,000 inhabitants, in 1975, the urban population raised to the 50%: Spain was no more rural to become an industrial and urban country (Fusi *et al.*, 1983).

During the two last decades of the 20<sup>th</sup> Century, the Zipf's parameters change the 80-years decreasing tendency by a noteworthy increasing one. That is to say, the group of 722 urban municipalities displayed a clear convergence pattern of growth since the smallest towns grew faster than the largest cities. Actually, Spain lived a strong counter-urbanization process than has not finished yet. By the beginning of the 80's, there was a peculiar urban structure similar to a star, with its centre in Madrid (Informe Foessa, 1970). In the axis, there were the vast Mediterranean metropolitan areas (Girona-Barcelona-Tarragona, Castellón-Valencia-Alicante-Murcia), Andalusia (Seville and Cádiz), Galicia (A Coruña-Ferrol, Vigo) and the

Cantabric Coast (Bilbao-San Sebastián, Santander, Gijón-Oviedo). In addition, inside this big star, there was a big rural desert, only broken by a few urban oases, like Valladolid, Saragossa, Badajoz, Burgos, Vitoria and Pamplona. In the Islands, we had a similar process due to the huge growth of Palma (the Balearics), Las Palmas and Santa Cruz de Tenerife (the Canary Islands). The cities of Madrid and Barcelona grew towards their respective peripheries and so did -with less strength- Valencia and Bilbao. Indeed, the whole Bask Country was declared an "urban area", as well as the triangle Oviedo-Gijón-Avilés (in Asturias) and the cities along the Mediterranean coast from Tarragona (in Catalonia) to Cartagena (in Murcia).

The logical problems of the big cities (with an uncontrolled growth in the peripheries and an incipient depopulation process of their historical centers) broke their later expansion in favor of middle-sized -even small- cities and certain rural areas. Moreover, this des-urbanization of the largest cities became a "metropolization" of their neighbor towns: suburban settlements gained many people and city centers were depopulated, restored and converted into CBD's and/or historical/cultural cores.

### **3. MOBILITY WITHIN THE SPANISH URBAN SYSTEM 1900-2001**

The density functions and Zipf's law allow characterizing the evolution of the global distribution, but they do not provide any information about the movements of the urban municipalities within this distribution. Indeed, they do not say whether the right tail of the initial distribution (year 1900) contains the same regions as the right tail in the final distribution (year 2001). A possible way to answer these questions is to track the evolution of each urban municipality's relative size over time by estimating transition probability matrices associated to Markov chains (Kemeny and Snell, 1976).

#### **3.1. Markov Chains**

Denote  $F_t$  the cross-sectional distribution of municipal size (population) at time  $t$  relative to the Spanish average. Define a set of  $K$  different size classes, which provide a discrete approximation of the population distribution. We assume that the frequency of the distribution follows a first-order stationary Markov process. In this case, the evolution of the municipal size distribution is represented by a transition probability matrix,  $M$ , in which each element  $(i, j)$  indicates the probability that a municipality that was in class  $i$  at time  $t$  ends up

in class  $j$  in the following period<sup>6</sup>. Formally, the  $(K, 1)$  vector  $F_t$ , indicating the frequency of the urban municipalities in each class at time  $t$ , is described by the following equation:

$$F_{t+1} = MF_t \quad (5)$$

where  $M$  is the  $(K, K)$  transition probability matrix representing the transition between the two distributions as follows:

$$M = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1K} \\ p_{21} & p_{22} & \dots & p_{2K} \\ \dots & \dots & \dots & \dots \\ p_{K1} & p_{K2} & \dots & p_{KK} \end{bmatrix} \quad (6)$$

where each element  $p_{ij} \geq 0$ ,  $\sum_{j=1}^K p_{ij} = 1$ . The stationary transition probabilities  $p_{ij}$  capture the probability that the class  $i$  in  $t-1$  is followed by state  $j$  in  $t$ .

The elements of  $M$  can be estimated from the observed frequencies in the changes of state from one period to another. Thus, following Amemiya (1985) or Hamilton (1994), the maximum likelihood estimator of  $p_{ij}$  is:

$$\hat{p}_{ij} = \frac{n_{ij}}{n_i} \quad (7)$$

where  $n_{ij}$  is the total number of urban municipalities moving from class  $i$  in decade  $t-1$  to class  $j$  in the immediate following decade  $t$  over all the 10 decades of transitions and  $n_i$  is the total sum of municipalities ever in  $i$  over the 10 decades.

If the transition probabilities are stationary, that is, if the probabilities between two classes are time-invariant, then:

$$F_{t+s} = M^s F_t \quad (8)$$

In this framework, one can determine the ergodic distribution (also called the long-term, long-run, equilibrium or steady state distribution) of  $F_t$ , characterized when  $s$  tends toward infinity in equation 8, that is to say, once the changes represented by matrix  $M$  are repeated an arbitrarily number of times. Such a distribution exists if the Markov chain is regular, that is, if and only if for some  $m$ ,  $M^m$  has no zero entries. In this case, the transition probability matrix converges to a limiting matrix  $M^*$  of rank 1.

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<sup>6</sup> The so-called Markov property implies that the future of a process depends only on its present state and not on its history.

The existence of an ergodic distribution,  $F^*$ , is then characterized by:

$$F^*M = F^* \quad (9)$$

This vector  $F^*$  describes the future distribution of the urban municipalities if the movements observed in the sample period are repeated to infinity. Each row of  $M_t$  tends to the limit distribution as  $t \rightarrow \infty$ . According to equation 9, this limit distribution is therefore given by the eigenvector associated with the unit eigenvalue of  $M$ .

The assumption of a first-order stationary Markov process requires the transition probabilities,  $p_{ij}$ , to be of order 1, that is, to be independent of states at the beginning of previous periods (at time  $t - 2, t - 3, \dots$ ). If the chain is of a higher order, the transition matrix will be misspecified. It will contain only part of the information necessary to describe the true evolution of the population distribution. Moreover, the Markov property implicitly assumes that the transition probabilities,  $p_{ij}$ , depend on  $i$  (i.e., that the process is not of order 0).

In order to test this property, Bickenbach and Bode (2003) propose a **test of time independence**. In determining the order of a Markov chain, they suggest, first, to test order 0 versus order 1; second, to test order 1 versus order 2; and so on (Tan and Yilmaz, 2002). If the test of order 0 against order 1 is rejected, and the test of order 1 against order 2 is not rejected, the process may be assumed to be of order 1.

To test for order 0, the null hypothesis  $H_0 : \forall i : p_{ij} = p_j (i = 1, \dots, K)$  is tested against the  $H_a : \exists i : p_{ij} \neq p_j$ . The appropriate likelihood ratio (LR) test statistic reads as follows:

$$LR^{(o(0))} = 2 \sum_{i=1}^K \sum_{j \in A_i} n_{ij}(t) \ln \frac{\hat{p}_{ij}}{\hat{p}_i} \sim asy \chi^2 \left[ (K-1)^2 \right] \quad (10)$$

assuming that  $\hat{p} > 0, \forall j (j = 1, \dots, K)$ .  $A_i = \{j : \hat{p}_{ij} > 0\}$  is the set of nonzero transition probabilities under  $H_a$ .

To test for order 1 versus 2, a second-order Markov chain is defined by also taking into consideration the population size classes  $k (k=1, \dots, K)$  in which the regions were at time  $t-2$  and assuming that the pair of successive states  $k$  and  $i$  forms a composite state. Then, the probability of an urban municipality moving to state  $j$  at time  $t$ , given it was in  $k$  at  $t-2$  and in  $i$  at  $t-1$ , is  $p_{kij}$ . The corresponding absolute number of transitions is  $n_{kij}(t)$ , with the marginal frequency being  $n_{ki}(t-1) = \sum_j n_{kij}(t-1)$ .

To test  $H_0 : \forall k : p_{kij} = p_{ij} (k = 1, \dots, K)$  against  $H_a : \exists k : p_{kij} \neq p_{ij}$ , the  $p_{kij}$  are estimated as  $\hat{p}_{kij} = n_{kij} / n_{ki}$ , where  $n_{kij} = \sum_{t=2}^T n_{kij}(t)$  and  $n_{ki} = \sum_{t=2}^T n_{ki}(t-1)$ . The  $p_{ij}$  are estimated from the entire data set as  $\hat{p}_{ij} = n_{ij} / n_i$ . The appropriate LR test statistic reads as follows:

$$LR^{(o(1))} = 2 \sum_{k=1}^K \sum_{i=1}^K \sum_{j \in C_{hi}} n_{kij} \ln \frac{\hat{p}_{kij}}{\hat{p}_{ij}} \sim asy \chi^2 \left[ \sum_{i=1}^K (c_i - 1)(d_i - 1) \right] \quad (11)$$

Similar to the notation above,  $C_i = \{j : \hat{p}_{ij} > 0\}$ ,  $c_i = \#C_i$ ,  $C_{ki} = \{j : \hat{p}_{kij} > 0\}$  and  $d_i = D_i = \{k : n_{ki} > 0\}$ .

If both Markovity of order 0 and of order 1 are rejected, the tests can be extended to higher orders by introducing additional dimensions for population size at time  $t-3$ ,  $t-4$ , and so on. However, since the number of parameters to be estimated increases exponentially with the number of time lags, while the number of available observations decreases linearly for a given data set, the reliability of estimates and the power of the test decrease rapidly. Therefore, Tan and Yilmaz (2002) suggest setting an a priori limit up to which the order of the Markov chain can be tested.

### 3.2. Empirical results

We distinguish between six different classes: (1) less than 20 percent of the Spanish average, (2) between 20 and 50 percent of the Spanish average, (3) between 50 and 80 percent of the Spanish average, (4) between 80 and 135 percent of the Spanish average (5) between 135 and 185 percent of the Spanish average, and (6) more than 185 percent of the Spanish average. The discretization has been chosen attending to the best performance of the test for first-order, though we have tried to set up balanced classes even if it comes at the cost of this test<sup>7</sup>.

Table 2 contains the first-order transition probability matrix between 1900 and 2001 with the maximum likelihood estimates  $\hat{p}_{ij}$  of the transition probabilities for population. For example, during the century period, there were 2,567 instances of an urban municipality having a population size lower than 20 percent of the Spanish average. The majority of these municipalities (94.4 percent) remained in that size class at the end of the year, while 5.3

<sup>7</sup> The first-order test (against the second order) is a test of time homogeneity (time stationarity), which is appropriate for deciding whether the transition probabilities of the first-order Markov chain can be assumed constant over time (Bickenbach and Bode, 2003).

percent moved up one class by the end of the year. Note also that the transition probability matrix is regular.

**Table 2 Probability transition matrix, 1900-2001: Spain-relative population size**

	<b>1</b> <20%	<b>2</b> <50%	<b>3</b> <80%	<b>4</b> <135%	<b>5</b> <185%	<b>6</b> >185%	<b>Number of observations</b>
<b>1</b>	0.944	0.053	0.002	0	0	0	2567
<b>2</b>	0.040	0.879	0.074	0.005	0.002	0.001	1751
<b>3</b>	0	0.162	0.752	0.078	0.005	0.003	1029
<b>4</b>	0	0.001	0.184	0.741	0.066	0.008	852
<b>5</b>	0	0	0	0.273	0.632	0.095	315
<b>6</b>	0	0	0	0.001	0.061	0.938	706

We can make several comments about this matrix in Table 2, related to the interclass movements, mobility speed, convergence pattern and influence of space.

First, the elevated probabilities on the diagonal show a **low interclass mobility** –i.e., a high-persistence of urban municipalities to stay in their own class from one decade to another over the whole period. However, the larger and smallest urban municipalities (classes 1 and 6, respectively) have higher persistence while medium-sized cities (categories 3, 4 and 5) have more probability to move to smaller categories. In addition, in classes 2 and 3, a small number of urban municipalities move up to higher categories more than two steps, even reaching the top, whilst they only move down one cell. Nevertheless, only in class 2 the probability of moving up a state exceeds that of moving down.

For the process in Table 2, Markovity of order 0 is tested by comparing each row of the transition matrix to the population distribution at time  $t$  using the test statistic (10). The result ( $LR = 16,602.90$ ;  $prob=0$ ;  $df=25$ ) leaves no doubt that the process strongly depends on the initial condition at time  $t-1$ , i.e. that the chain is at least of order 1.

To test Markovity of order 1, six subsamples  $k=1, \dots, 6$  are defined, representing the urban municipalities' size at time  $t-2$ . Observations for municipalities that were in the first size class at time  $t-2$  are allocated to the first subsample ( $k=1$ ) and so on. For each of these subsamples, a separate matrix is estimated for observed transitions from time  $t-1$  to  $t$  in the usual way. The general test comparing the matrices for all five subsamples to the matrix for the entire sample simultaneously, similar to equation (11) above, results in  $LR = 198.12$ . This statistic is highly significant with 63 degrees of freedom ( $prob=0$ ), indicating that the process under consideration is of a higher order, at least of order 2, if Markovian at all. However,

there are a number of classes within subsamples for which we cannot expect reliable estimates of transition probabilities because there are only very few observations available. In addition, this LR statistic seems to be inflated in presence of spatial autocorrelation, which is proved to exist. So that, we keep the assumption of order 1 for the Markov chain.

Second, in order to determine the **speed with which the urban municipalities move within the distribution**, we consider the matrix of mean first passage time  $M_p$ , where one element  $M_{p,ij}$  indicates the expected time for a region to move from class  $i$  to class  $j$  for the first time. For a regular Markov chain,  $M_p$  is defined as (Kemeny and Snell 1976, chap. 4):

$$M_p = (I_K - Z + SS'Z_{dg})D \quad (12)$$

where  $I_K$  is the identity matrix of order  $K$ ,  $Z$  is the fundamental matrix:  $Z = (I_K - M + M^*)^{-1}$ ,  $M^*$  is the limiting matrix,  $S$  is the unit vector,  $Z_{dg}$  results from  $Z$  setting off-diagonal entries to 0, and  $D$  is the diagonal matrix with diagonal elements  $1/m_j^*$ .

**Table 3 Mean first passage time matrix in decades, 1900-2001: Spain-relative population**

	1 <20%	2 <50%	3 <80%	4 <135%	5 <185%	6 >185%
1	3.93	18.67	39.00	78.88	158.83	311.07
2	51.88	2.82	21.99	62.01	142.50	294.48
3	63.87	11.99	5.53	45.12	127.61	279.61
4	73.55	21.67	9.90	10.20	95.73	251.82
5	82.74	30.86	19.08	9.19	28.87	189.41
6	98.57	46.69	34.92	25.02	18.22	12.89

Table 3 displays the matrix of mean first passage time for population. The mean number of years to reach any class is relatively high: the shortest passage of time is 91.9 years and the largest is 3110.7 years. Globally, movements up are slower than movements down, especially for high-size classes –i.e., the expected time to first move from class 5 to class 6 is 1,894.1 years. Remember that these calculations account for the fact that starting from class 5, a site might visit classes 4, 3, 2 or 1 before going to class 6. From class 1 it is 3,110.7 years to first visit class 6. This result of faster declines shows that urban municipalities are more likely to loose population than to gain it, especially in the inlands, big capitals and old industrial



centers<sup>8</sup>. This conclusion is compatible with the 80-year phase of divergence –in size– between urban municipalities, only reversed during the last two decades, as pointed out by the Zipf’s parameter in Figure 2.

Third, we consider the ergodic distribution that can be interpreted as the long-run equilibrium urban municipality-size distribution in the urban areas system. Explicitly, given a transition matrix, if many periods pass, there will be a time where the distribution of urban municipalities will not change any more: that is the ergodic or limit distribution. It is used to asses the **form of convergence in a distribution**. Concentration of the frequencies in a certain class would imply convergence (if it is the median class, it would be convergence to the mean), while concentration of the frequencies in some of the classes, that is, a multimodal limit distribution, may be interpreted as a tendency toward stratification into different convergence clubs. Finally, a dispersion of this distribution among all classes is interpreted as divergence.

**Table 4 Initial versus ergodic distributions 1900-2001: Spain-relative population size**

	<b>1</b> <20%	<b>2</b> <50%	<b>3</b> <80%	<b>4</b> <135%	<b>5</b> <185%	<b>6</b> >185%
Initial distribution	0.356	0.243	0.143	0.118	0.044	0.098
Ergodic distribution	0.254	0,355	0,181	0,098	0,035	0,078

Ergodic distributions are computed for population size in Table 4. It appears that the ergodic distribution is more concentrated in the small-size municipalities (1<sup>st</sup> and 2<sup>nd</sup> classes) what would reveal the existence of convergence towards smaller-size populations. In addition, we find stability of ergodic distribution compared to the initial one, though there is slightly more probability in category 2. This outcome points out a very slight downward convergence, what is compatible with the kernel density function (Figure 1) and transition matrix (Table 2) results.

Fourth, we have computed the **influence of space** on the transition probabilities, as in Rey (2001). The relationship between the direction of an urban municipality’s transition in the population distribution and the relative populations of its neighbors is considered more generally in Table 5. Reported is the probability of a particular transition (Down, None, or Up) conditioned on the populations of the urban municipality’s neighbors at the beginning of

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<sup>8</sup> Again, this result contrasts with the US metro areas behavior (Black and Henderson, 2003; pp. 358)

the year. There is clear evidence that the probability of an upward or downward move is different depending on the urban area context. For example, the probability for an urban municipality of moving up in the hierarchy is 7.1% when the spatial lag contains on average less population whereas it is 8% when it contains on average more population. Conversely, the probability for an urban municipality of moving down in the hierarchy is 18.9% when the spatial lag contains on average less population whereas it is only 3.9% (almost five times lower) when it contains on average more population. Therefore, the influence of space on the urban municipality transition probabilities seems more important for downward movements.

There seems to be an influence of neighbors, which is confirmed by the  $\chi^2$  test statistic of independence of direction of move and neighbors population size, with 4 degrees of freedom, generated a value of 398.087, which is significant at  $prob=0$ . In conclusion, direction of movement in the population distribution of urban municipalities is not independent from the geographic environment.

**Table 5 Transition probabilities conditioned on the spatial lag of population**

spatial lag	Move		
	<i>down</i>	<i>same</i>	<i>up</i>
<i>Less population</i>	0.189	0.740	0.071
<i>Same</i>	0.057	0.898	0.045
<i>More population</i>	0.039	0.881	0.080

#### 4. MAIN CONCLUSIONS

The urbanization process has mainly taken place during the 20th century producing significant processes of industrialization and economic growth. Specifically in Spain, this process has not been uniform and exhibits different shapes depending on the definition of “urban area”. In our case, we work with a set of 722 municipalities that conforms the Spanish urban areas: main cities and their satellite towns.

The Zipf’s law shows the existence of two main phases in the evolution of these urban municipalities: 1900-1980 (divergence) and 1980-2001 (convergence). The main one extends over 80 years and consists of a reduction of urban concentration, though two different sub-periods should be distinguished: 1900-1940 and 1940-1980. In effect, from 1900 to the 30’s, divergence is not so deep coinciding with a significant industrialization and urbanization expansion that led to progress and social changes. However, this dynamism is violently

broken by the end of the decade due to the Civil War. From 1940 to the 70's, the largest cities grew much quicker than the smallest population nuclei, what led to a more intense divergent pattern of growth.

During the last decades of the 20<sup>th</sup> Century, the Zipf's parameters change the 80-years decreasing tendency by a noteworthy increasing one. That is to say, the group of 722 urban municipalities displayed a clear convergence pattern of growth since the smallest towns grew faster than the largest cities. The logical problems of the big cities (with an uncontrolled growth in the peripheries and an incipient depopulation process of their historical centers) broke their later expansion in favor of middle-sized -even small- cities and certain rural areas. Moreover, this des-urbanization of the largest cities became a "metropolization" of their neighbor towns: suburban settlements gained many people and city centers were depopulated, restored and converted into CBD's and/or historical/cultural cores.

The Markov Chains analysis shows a low interclass mobility –i.e., a high-persistence of urban municipalities to stay in their own class from one decade to another over the whole period. However, the largest and smallest urban municipalities have higher persistence than the medium-sized cities, which have more probability to move to smaller categories. In general terms movements up are slower than movements down, especially for high-size classes. This result of faster declines shows that urban municipalities are more likely to loose population than to gain it, especially in the inlands, big capitals and old industrial centers. This conclusion is compatible with the 80-year phase of divergence –in size- between urban municipalities, only reversed during the last two decades. This is why population convergence is still slight and mainly “downwards” inside the group of urban municipalities.

Finally, the probability for an urban municipality of loosing population (moving down in the hierarchy) is almost five times higher when it is surrounded by towns that contain on average less population. This result confirms the influence of space on urban population dynamism, also being more important for downward movements.

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