The geography of Spanish bank branches: a Bayesian perspective

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Abstract

This paper analyzes the determinants of bank branch location in Spain taking the role of geography explicitly into account. After a long period of intense territorial expansion, especially by savings banks, many of these firms are now involved in merger processes triggered off by the financial crisis, most of which entail the closing of many branches. However, given the contributions of this type of banks to limit financial exclusion, this process might exacerbate the consequences of the crisis for some disadvantaged social groups. Related problems such as new banking regulation initiatives (Basel III), or the current excess capacity in the sector add further relevance to this problem. We address the issue from a Bayesian spatial perspective, which has several advantages over other methodologies used in previous studies. Specifically, the techniques we choose allow us to assess with some precision whether over-branching or under-branching have taken place. Our results suggest, among other findings, that both phenomena are present in the Spanish banking sector, although the implications for the three types of banks in the industry, namely, commercial banks, savings banks or credit unions, vary a great deal.

Key words and phrases: bank, Bayesian statistics, branch, municipality

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1. Introduction

During the last few years the geography of bank branches has been changing in several countries around the world. In the US, the McFadden Act of 1927 had prohibited commercial banks from operating across state lines, and state laws went even further by restricting banks' ability to set up branches across county lines (DeYoung et al., 2004). The Riegle-Neal Act of 1994 replaced the McFadden Act, ultimately removing branching restrictions at both intra- and inter-state levels. These deregulatory initiatives generated a remarkable body of literature examining the different consequences for the banking industry, both for the financial institutions themselves (see, for instance Berger and DeYoung, 2001) and the US economy (see, for instance Jayaratne and Strahan, 1996; Huang, 2007), among other relevant issues (Berger et al., 1995).

From a European point of view, analogously to what happened in the US, the passing of a similar law to the Reagle-Neal act in Spain,[1] which has one of the five largest banking systems in Europe, allowed savings banks to enter other markets different to their traditional ones, since they were authorized to set up offices in regions which were different from their regions of origin (Illueca et al., 2009). This deregulatory banking initiative triggered off the reshaping of the geography of Spanish banking in which, simultaneously to the Latin America forays of some large commercial banks (the Spanish Banco Santander and BBVA are the largest banks in Latin America), savings banks expanded geographically throughout the country, becoming the main actors in dimensions as important as the total number of branches, especially for retail banking.

The recent economic and financial crisis might have put into question the validity of the geographical expansion policies followed by most savings banks which, together with private commercial banks and credit unions, constitute the Spanish banking system. However, in terms of geographical expansions into other territories, savings banks have been much more active than other types of banks because of the regulatory constraints these firms faced in this respect prior to 1989. Many of these firms based their expansion on inflating the housing bubble, whose burst is closely related to the difficulties some of these banks have been going through in recent times. As a result of such difficulties, the 46 savings banks existing by the end of 2009 have been reduced to 17 due to the restructuring process enforced by the Bank of Spain, whose principal aim was to strengthen the Spanish financial system. In addition, prior to the start of this restructuring process, some savings banks had already initiated a sort of

[1] Real Decreto 1582/1988.

back off policy by closing some offices—the total number of bank branches in Spain started to decline in 2008, and the decline has intensified in 2009 and 2010, as we shall see below. The total number of bank branch offices can therefore be forecast to decrease further in the next few years, not only for savings banks but also for commercial banks and credit unions.[2]

However, since this pattern is not expected to reverse but, on the contrary, to worsen further, and some concerns might be raised about its likely negative effects. In a recent study, Bernad et al. (2008) analyzed the possible long-term consequences of deregulation on financial exclusion in Spain. In their conclusions, as well as in other parts of the paper, it is stressed that both savings banks and credit unions are the main contributors to financial inclusion. Although some authors such as Okeahalam (2009) have pointed out how relevant financial exclusion can be in developing countries, its importance cannot be neglected in more advanced economies either. As indicated by Carbó et al. (2005), the low use and lack of banking services designed specifically for vulnerable groups is inherent to European Union countries such as Spain, Greece, Ireland and Italy (Carbó et al., 2005, p.106). In the particular case of Spain, although financial exclusion has not been high on the political agenda—at least in comparison with other countries—various institutions have pursued objectives aimed at helping to reduce it. In particular, Spanish savings banks offer banking products that are designed specifically for vulnerable groups, which is in line with the results by Bernad et al. (2008).

The recent study by Alamá and Tortosa-Ausina (2011) provides an extension to the one by Bernad et al. (2008) by enlarging the set of socioeconomic variables included in the analysis, considering a different approach (quantile regression) which enables a better understanding on how the impact of each covariate may affect the tails of the distribution differently. Both the papers by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011) use the same database, developed by the foundation of the Spanish savings bank *La Caixa*,[3] which provides information at a municipal level. However, this database does not take into consideration the exact *geographical* component of the location of bank branches. Therefore, it excludes the information on the precise location of each bank branch. In that sense, our paper is closer to the proposal by Okeahalam (2009), who analyzes not only how socio-economic variables might affect the number of branches in a given municipality but, more specifically, the association between these variables and the *spatial* distribution of branches in South Africa. Specifically, that author con-

[2]According to the calculations of the Bank of Spain, in compliance with the provisions of law Real Decreto-Ley 2/2011 of 18 February 2011 for the reinforcement of the Spanish financial system, twelve banks had to increase their capital (to an amount totaling €15.15 billion), two of which were Spanish commercial banks, two were subsidiaries of foreign banks and eight were savings banks.

[3]URL:`http://obrasocial.lacaixa.es/laCaixaFoundation/home_en.html`.

siders parametric Poisson, negative binomial, Poisson-hurdle, and finite-mixture count models for analyzing retail bank branch location, since those models can control for unobserved heterogeneity.

In a different fashion, our study considers a Bayesian *spatial* approach which has some interesting advantages. One of them, of particular interest to us, is the possibility of testing for the existence of either *under-* or *over-branching*, which are important problems now in the Spanish savings bank sector, for various reasons. Under-branching, might be related to the problem of financial exclusion. Apart from the studies cited in the previous paragraphs, which focus mainly on the case of Europe, there is additional relevant literature analyzing different aspects of this issue, including Dymski and Veitch (1996), Pollard (1996), Leyshon and Thrift (1995), Leyshon and Thrift (1996), or Marshall (2004), among others. More recently, as previously indicated, Carbó et al. (2005, 2007) have analyzed how important this matter may be in the context of European banking. In the particular case of Spain, which has one of the five largest banking systems in Europe, and where the intensity of the economic and financial crisis is particularly severe, the previously cited papers by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011) deal with the issue, but only *partially*—at least from a *geographical* point of view. Specifically, they exclude a non-negligible number of municipalities. In particular, *La Caixa* database, used both by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011), includes only those municipalities with a population above 1,000. This implies excluding a relevant number of municipalities which might not be very large in terms of population, but of remarkable importance in terms of land occupied.

In contrast, over-branching may also have been an important issue due to the restructuring process in the Spanish banking sector, which is taking place now due to the excess capacity of several banks. This has been a recurrent problem in banking, as reported in several contributions such as Shaffer (1996), Bikker et al. (2000) or Amable et al. (2002). The recent economic and financial crisis has severely affected many Spanish financial institutions, especially savings banks, and as a result, the sector is going through intense restructuring. The Royal Decree-Law 9/2009 of 26 June 2009 (FROB Law) laid the legal foundations for the reshaping of the savings bank sector which is resulting in a sharp decline in the number of savings banks. Most of them will ultimately operate as commercial banks, and consequently their contribution to financial inclusion might be thwarted. The institutions involved in each particular merger come from different regions and, therefore, the links with the local and regional economies of the resulting bank will be much weaker than those of the merging institutions.

Therefore, taking into account both the relevance of financial exclusion and recent changes in the banking industry in general, and in the geography of bank branches in particular, this article analyzes of the association between some socio-economic variables and the spatial distribution of bank branches in *all* Spanish municipalities. This will enable spatial effects to be dealt with more effectively, since each municipality will always be comparable with its neighbors, regardless of its population size. Since access to bank services is unlikely to be improved simply by an increase in the number of bank branches (which is not anticipated in the near future), the spatial distribution of branches need to address points of actual and growing unmet demand—which could also be points of declining demand.

The article is structured as follows. After this introductory section, Section 2 briefly reviews the literature on financial exclusion, and Section 3 provides some insights into the Spanish banking system and its financial institutions' policies on branches. Section 4 presents the details on the modeling of bank branches, whereas the empirical analysis is devoted to Section 5, which describes the data, and Section 6, which presents the results. Section 7 outlines some concluding remarks.

2. Financial exclusion and the availability of banking services: a brief review of the literature

The literature on the availability of banking services and financial exclusion is relatively scarce and the evidence, especially on availability, is more focused on the US case. Other contributions published for other contexts such as Europe are scarcer, probably because in the deregulation of bank branches experience has been more limited. A notable exception is Spain, the country on which we focus, where the deregulatory experience resembles what happened in the US.

Some of these references analyze explicitly the links between bank branch location decisions and financial service accessibility. For instance, Evanoff (1988) analyzes the impact of branching on the accessibility of banking services (measured as the proximity of facilities to the customer), finding that branching limitations are found to decrease the level of service availability significantly in both metropolitan and rural areas once economic and demographic factors are controlled for. Previously, Gilbert (1974), or Gilbert and Longbrake (1973) had found that facilities were more plentiful when branching was allowed. However, other authors such as Jacobs (1965), or Lanzillotti and Saving (1969), found that the relationship between branching restrictions and service availability might be more involved when the effect of branching was isolated from that of demographic differences among states.

After Evanoff's (1988) paper was published, the number of contributions focusing on this issue fell dramatically and, were also scattered over time. A few exceptions would include Garrett et al. (2005), who use a spatial probit model to investigate a state's choice of branch banking and interstate banking regimes as dependent on the regime choices made by other states, and other variables suggested in the literature. However, despite its relevant results, this is a study very specific to US conditions, whose application to other contexts is difficult due to the different regulations, and their attempts are not entirely coincidental with ours. In contrast, the relatively recent paper by DeYoung et al. (2004) is more closely related to our study, since the authors explore whether and how bank headquarter locations, bank branch office locations, and bank depositor locations changed during the 1990s—although they also consider some methods which differ markedly from the ones we use.

The methodologies used in the recent study by Okeahalam (2009), which is not focused on the US but on the case of South Africa, are much closer to ours, both in their aims and methods, since it undertakes an analysis of the association between socio-economic variables and the spatial distribution of bank branches. In that paper, the author proposes a count analysis, reaching some relevant findings which are in line with previous literature—namely, that the aggregate income in a municipal area is a statistically significant determinant of the number and distribution of bank branches.

Part of the literature on the determinants of bank branch (office) location has been concerned with the issue of financial exclusion. In this case, many contributions also focus on the European case. Some authors have dealt explicitly with this issue recently (Carbó et al., 2005, 2007), but relevant contributions had been published earlier. Among them, we should highlight not only those by Dymski and Veitch (1996), Pollard (1996), Leyshon and Thrift (1995), Leyshon and Thrift (1996), Marshall (2004), but also some others such as Joassart-Marcelli and Stephens (2010) who, (again) in a US context, focus on how the geographical dimensions of banking affect immigrants' lack of financial integration.

Finally, we should also refer to a very relevant literature which has also dealt with these issues, namely, that focusing on the finance-growth nexus and, more particularly, that focusing on the financial (branch) deregulation-growth nexus. In this literature some important contributions have been published focusing on the US case (Jayaratne and Strahan, 1996), and some others (much fewer) on the European case (Degryse and Ongena, 2005). However, the specific attempts of these contributions lie beyond the scope of our paper.

3. On the distribution of bank branches and municipalities in Spain

One of the main features of the Spanish banking system for many years—long before the deregulatory initiatives of the 1980s took place—has been its large number of bank branches per capita. This characteristic has been produced by all types of firms in the industry, namely, commercial banks, savings banks, and credit unions. In the years immediately preceding the start of the international crisis, this pattern was especially intense. In particular, the law that allowed these firms to expand geographically (Real Decreto 1582/1988), removing the barriers impeding their nationwide expansions, resulted in a sharp increase in the total number of savings bank branches, especially outside their regions of origin. Simultaneously, the total number of commercial bank branches actually *declined*.

Table 1 reports information on the evolution of the number of bank branches between 1986 (just before nationwide expansion was allowed for all banking firms) and 2010. The information is also detailed for the different types of banks that make up the Spanish banking industry. The total number of bank branches has increased dramatically, from 30,961 to 42,894, although it had peaked in 2008, when it reached 45,662 branches. This represents a hefty average annual increase of 1.37% between 1986 and 2010, but even higher between 1986 and 2008 (1.78%). In contrast, during the crises years (between 2008 and 2010) the total number of branches decreased sharply, and it is forecast to decline even further due to the restructuring in the savings bank sector.

As indicated above, the increase in the number of bank branches was mainly due to the geographical expansion of those banks which were not allowed to do so before 1989, namely savings banks. Their total number of branches more than doubled between 1986 (11,061 branches) and 2008 (24,985 branches), although it has declined sharply during the crisis' years, until 2010. Therefore, although the change between 1986 and 2008 was an annual 3.77% on average, the decline in the last two years has been 4.79%.[4] Due to this recent decline, the savings bank share of total bank branches, which had increased sharply, is backing off, although it is still, by and large, the group of banks with more branches—representing 52.8% of the total number of branches. Finally, the number of credit union branches has also increased substantially,

[4]It is also predicted to decline even more sharply in the next few years. For instance, Banco Sabadell, a Spanish commercial bank based in Catalonia, recently acquired one of the largest Spanish savings banks, Caja de Ahorros del Mediterráneo (CAM), and it has been announced that the number of branches of the acquired firm that will be closed should be at least 300. This will also imply a non-negligible reduction in the number of employees.

although, in contrast to what occurred with savings banks, they are going through a moderate decline in the total number of branches. Actually, their share of the total number of bank branches increased modestly from 1986 (10.3%) until 2010 (11.7%).

Table 2 reports information on the distribution of bank branches according to municipality size. This table clearly shows how peculiar the size distribution of Spanish municipalities is, since out of 8,109 municipalities, more than half (4,858) have fewer than 1,000 inhabitants, and almost 85% have fewer than 5,000. These municipalities also represent a hefty share of the total Spanish surface area, as also indicated in Table 2—38.12% for municipalities up to 1,000 inhabitants and 31.61% for those up to 5,000 inhabitants. In Figure 1 the area occupied by villages with a population under 1,000 is depicted in yellow and, as can be visually corroborated, it indeed represents a large part of Spain's total surface area. However, the percentage of the total population living in those towns is very small, representing less than 15% of the total Spanish population. The same pattern holds for municipalities with population between 1,000 and 5,000, which are depicted in orange in Figure 2.

The last columns in Table 2 provide some insights into the differing contributions of the three types of firms to financial inclusion. The percentage of commercial bank branches in villages with a population under 1,000 (0.81%) is proportionally much lower than that corresponding to the share of total population living in these villages (3.27%). In contrast, for both savings banks and credit unions the sign of these discrepancies is reversed, and it is especially high for the latter. For municipalities with a population between 1,000 and 5,000, commercial banks are still affected by *under-branching* (in the case of population only determining the number of branches), although to a much lesser extent. In contrast, the other types of banks still contribute to financial inclusion by branching more than proportionally with respect to population—cæteris paribus. However, the analysis of the number of bank branches per municipality depends on other factors that will be examined thoroughly in the ensuing sections.

4. Modeling the number of bank branches

In what follows, we introduce the underpinnings of our approach on how to model the number of bank branches on a given location. This will be done regardless of the type of bank, i.e., we are implicitly assuming that commercial banks, savings banks and credit unions can provide access to similar financial products and services. To do so, we have divided this section into two subsections. In the first one (Subsection 4.1) we briefly review those aspects of Bayesian statistics that will be helpful for us when making inference on the parameters that govern the model we propose. In the second one (Subsection 4.2) we present the model that will allow us to check, among other things, the possible existence of either under-branching (because of its implications for financial exclusion) or over-branching (because of its implication in terms of excess capacity).

4.1. Bayesian approach: some basic ideas

Bayesian statistics is founded on the fundamental premise that all uncertainties should be represented and measured by probabilities. On the one hand, traditional statistical methods make use of the data (basically) through the likelihood function, which depends on the selected probabilistic model and connect the data and the unknown parameters. On the other hand, Bayesian statistics is a more complex methodology that allows us to incorporate into the inferential process not only the data but also all the available prior knowledge about the unknown parameters. This information needs to be expressed in probabilistic language in the so-called prior distribution. The Bayes theorem combines both types of information and provides the posterior distribution, which contains all the relevant knowledge about the parameters of interest. In this sense, from the Bayesian point of view, there is no longer a necessity for *ad hoc* tests such as heterogeneity or normality tests, making the analysis simpler. In particular, Bayesian Hierarchical models are a powerful tool for constructing models for complex scenarios (see, for example Banerjee et al., 2004; Zhao et al., 2006). The results are expressed through posterior probability distributions, which contain all the relevant knowledge about the unknown quantities of interest.

The computation of posterior probability distributions is not always easy to deal with. In fact, these distributions cannot always be obtained in an analytical way. For many years, the computational challenge of obtaining posterior distributions has been one of the main issues for not using Bayesian statistics. But nowadays this task has been simplified by the increasing capacity of computers together with the development of simulation methodologies based on Montecarlo sampling and Markov Chain Monte Carlo (MCMC) (see Green, 2001, for example). These useful simulation procedures result in an approximate sample of the posterior distribution from which we can make inference (posterior means and medians, credible regions, quantiles, etc.) (Gammerman and Lopes, 2006). MCMC methods can be implemented in many statistical packages. In this paper we will use them through WinBUGS (Spiegelhalter et al., 2003), a statistical software which provides a simple implementation of a great number of complex statistical models.

One important issue that arises when using Bayesian statistics is that of objectivity. Many classical statisticians argue that using prior information may introduce some bias into the analysis. This is not entirely true. In this sense an Objective Bayesian approach can be adopted as shown in Berger (2006). Objective Bayesian statisticians argue that using a good "objective prior" results in the same conclusions as classical analysis while still enjoying the advantages of the Bayesian framework (see Berger, 2006).[5]

As happens in classical statistics, another relevant issue in Bayesian statistics is that of finding the best model to explain some data, usually known as model selection. Among the Bayesian criteria for model selection, two of the most popular ones are the Bayesian Information Criterion (BIC) (Schwarz, 1978) and the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002). Although both of them weigh up the goodness-of-fit and the complexity of the selected model, the more useful criterion when comparing models whose posterior distribution has been approximated by MCMC is DIC. This is the case in our paper, and consequently our selected criterion. The smaller the DIC, the better the fit.

4.2. Poisson regression

In order to describe the distribution of bank branches in each of the 8,109 Spanish municipalities[6] we consider Generalized Linear Mixed Models (see for instance McCulloch and Searle, 2001, for a description of these kind of models). Taking into account that our data can be seen as count data, we will use the framework of Poisson regression. In particular, similar to Okeahalam (2009), we consider that the observed number of bank branches in each municipality (O_i) follows a Poisson distribution with mean μ_i:

$$O_i \sim \mathrm{Po}(\mu_i), \quad i = 1, \ldots, 8109.$$

Since we consider that the number of bank branches depends, among other factors (as we shall see below), on the number of people having access to them, as indicated by the literature on service availability (see, for instance Evanoff, 1988) , and that there are large differences in population among municipalities, it makes no sense to model μ_i directly. Instead, we define $\mu_i = E_i \times \lambda_i$, where E_i is the *expected* number of branches in each municipality computed with

[5]An interesting discussion about Objective and Subjective Bayesian analysis can be found in Berger (2006) and Goldstein (2006), among others.

[6]Further specific details on the data and sample used will be discussed in Section 5.

respect to the corresponding population, in such a way that:

$$E_i = \text{Population living in each municipality } i \times \frac{\text{Total number of bank branches in Spain}}{\text{Total population in Spain}},$$

and λ_i is a parameter modifying the expected number E_i, representing how many times the *observed* number of branches is larger (smaller) than the *expected* one. In other words, λ_i measures what we could refer to as over-branching (under-branching).

As usual in Poisson regression, the log-link is used to relate the average number of branches (μ_i) to potential causes. Hence, the next step would be modeling $\log(\mu_i)$, in our case $\log(\lambda_i)$. To do so we need to enquire about what effects are involved in this modeling. These can be fixed (as covariates or factors) and/or random effects. In our study of the number of bank branches we consider the existence of three main possible sources of variability: some covariates (which we choose based on previous literature), a random effect per municipality, and some other possible geographical effects involved. In the next section we will study these three effects in detail. Therefore, with respect to the existing literature, we are considering not only the impact of covariates but also two additional effects.

However, given that we have a particular interest in the *geographical* component of bank branch location, we will specifically include information in this respect. Therefore, the empirical strategy will differ greatly from previous approaches, since it will have a structure made of three components: (i) covariates; (ii) random effect per municipality; and (iii) geographical effect.

Covariates The first source of variability, as mentioned above, is the one related to *covariates*, or *factors*. Specifically, for this study we have considered the population density in logarithmic scale, the unemployment (in percentage) and the foreign population (in percentage) as covariates.[7]

Denoting $\boldsymbol{X}_i$ as the vector of covariates measured in municipality i, we model $\log(\lambda_i)$ as:

$$\log(\lambda_i) = \boldsymbol{X}_i^t \boldsymbol{\alpha} \,. \tag{1}$$

Random effect per municipality It is worth noting that if we were modeling Poisson data, their mean and variance should be similar. But, as is the case in many studies, our data do

[7]Previous studies have also considered the total population. However, this information is already available in our model.

not follow this rule. In fact, the variance of our data is quite a bit larger than the mean. This over-dispersion is the main reason why we consider it necessary to include a random effect per municipality in the Poisson regression. In particular, adding an independent random effect per municipality, Equation (1) becomes:

$$\log(\lambda_i) = \boldsymbol{X}_i^t \boldsymbol{\alpha} + U_i \tag{2}$$

where, $\boldsymbol{U} = (U_1, \ldots, U_{8109})$ is the vector of independent random effects where each U_i is independently and identically distributed (i.i.d.):

$$U_i \sim N(0, \sigma_U^2), \; i = 1, \ldots, 8109. \tag{3}$$

Geographical effect The third possible source of variability that we consider when explaining the number of bank branches in each municipality is the likely effect of the geographical units into which the country is divided. In the particular case of Spain we are dealing with there are two basic levels of geographical units apart from the municipalities, namely regions (which correspond to NUTS[8] level 2) and provinces (which correspond to NUTS level 3).[9]

However, it is not *a priori* evident whether this effect is at the region or at the province level. Neither is it evident whether this effect enters the analysis as a factor (or fixed effect), as an independent random effect or as a random effect with a dependence structure. Therefore, in order to determine which the best option is (combination of the level and the type of effect) we perform a *model selection based on DIC*, and let the data inform us about this issue. In what follows we just briefly describe the three possible types of effects and leave the selection for Section 6.

Explaining the geographical effect as fixed effects is equivalent to considering k different dummy variables, one per geographical unit. According to this, each observation O_i corresponding to municipality i will have an effect β_j due to being located in the geographical unit j. In order to avoid collinearity, fixed effects are considered for $k-1$ of the k geographical units, with the

[8]NUTS stands for Nomenclature of Territorial Units for Statistics. See the web page `http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction` for more information. Municipalities corresponded to NUTS level 5 until 2003. Since then, both levels 4 and 5 have been replaced by Local Administrative Units (LAUs). In the case of Spain, provinces (NUTS level 3) correspond to LAU level 1, and municipalities correspond to LAU level 2.

[9]Although before 1988 savings banks were already allowed to expand geographically within their home regions, this was actually done only at moderate rates—although it also depended on the particular savings bank considered. In addition, previous regulations had prevented them from expanding outside their provinces. Therefore, we consider a geographical effect constrained to the province because of the traditionally tighter links with their closest territorial units, which are the provinces.

remaining one being considered as base unit. Hence the fixed effect β_j of each geographical unit will indicate the deviation with respect to the value of the base unit (which is usually taken to be the one with the larger number of observations). Adding this effect, Equation (2) becomes

$$\log(\lambda_i) = \boldsymbol{X}_i^t \boldsymbol{\alpha} + U_i + \boldsymbol{Z}_i^t \boldsymbol{\beta} \tag{4}$$

where $\boldsymbol{Z}_i$ is a $(k-1)$-vector with value 0 in every position except for the one corresponding to the geographical unit of municipality i which has value 1. The presence of a geographical fixed effect would indicate specific differences among geographical units. This sort of effect can indicate that something is happening in one unit which makes it different to the rest.

We can also model geography via *independent random effects*. This sort of effect will indicate that there are no real differences (in terms of bank branches) among units, and that those differences are just due to randomness. This effect assumes explaining extra variability, as was the case for the municipality random effect, but at the geographical unit level. Adding this effect, Equation (2) becomes

$$\log(\lambda_i) = \boldsymbol{X}_i^t \boldsymbol{\alpha} + U_i + V_{\text{unit}_i} \tag{5}$$

where unit_i is the corresponding geographical unit of municipality i and $\boldsymbol{V} = (V_1, \ldots, V_j, \ldots, V_p)$ is a vector of random effects with p being the number of units. In particular, as in the case of random effects per municipality, each V_j is i.i.d. $N(0, \sigma_V^2)$.

Finally, geographical effects can also be modeled considering dependent random geographical effects. This sort of effects is considered when there is a dependence structure among geographical units. The model for $\log(\lambda_i)$ in this case is:

$$\log(\lambda_i) = \boldsymbol{X}_i^t \boldsymbol{\alpha} + U_i + W_{\text{unit}_i} \tag{6}$$

where $W = (W_1, \ldots, W_j, \ldots, W_p)$ is the vector of dependent random effects, one per unit. Conditionally autoregressive models (CAR) are the most popular distributions for modeling these spatially correlated random effects. These models were introduced by Besag (1974), but their use has spread extensively in the last 15 years. In particular, with this approach each W_j is normally distributed given $\boldsymbol{W}_{-j} = (W_1, \ldots, W_{j-1}, W_{j+1}, \ldots, W_p)$ as:

$$[W_j \mid \boldsymbol{W}_{-j}] \sim N\left(\sum_{m \neq j} \frac{\omega_{jm} W_m}{\omega_{j+}}, \; \frac{\sigma_Z^2}{w_{j+}} \right), \tag{7}$$

where ω_{jm} are the elements of a proximity matrix $\mathbf{\Omega}$ which gives a measurement of the relationship among regions, $\omega_{j+} = \sum_m \omega_{jm}$ and σ_W^2 is a variance parameter. Thus each spatial effect W_j, conditional on the remaining provinces, is normally distributed with a mean that depends on the neighboring provinces whose influence is weighted in the sense of how close they are to element j. The neighbors for a given municipality or province are chosen by adjacency, and consequently it is considered that two provinces or municipalities are neighbors if they have a common border.

To perform the Bayesian analysis we should consider a prior distribution for each unknown parameter in the model. In particular, for this study, we consider priors which contain little information and leave the lowest possible trace on the posterior. We adopt this "objective" point of view because we do not have much prior information apart from the one used in the choice of the model and the covariates.[10]

5. Data, variables and sources

The data on the geographical location of bank branches are provided by the Guía de la Banca, published by Maestre Edibán.[11] This data set corresponds to years 2004 and 2008, and contains information on the precise location (postal address) of every bank branch in Spain for selected years. This information is also available for other years (from 1992 to 2011). However, other variables used in the study are only available for a few periods, constituting an important determining factor which determines the time coverage of the study. Specifically, the last year for which data for unemployment at a municipal level was available was 2008.

Nonetheless, these years correspond to relevant periods, since 2004 is a year in which the Spanish economy was surging, whereas 2008 corresponds to the year in which the financial crisis started. Although, ideally, it would have been even more interesting to have information as updated as possible, in order to examine the effects of the crisis in more detail, the years examined contain enough information relevant to make our study interesting *per se*.

Table 3 reports information for all the variables used in the study and for the selected periods. This information is provided for each province (*provincias*) and each region (*comunidades autónomas*), in order to report it in a condensed way.

As indicated in the previous sections, the literature has been considering a number of factors that may determine the number of bank branches in a given location. In the particular

[10]For more information about the specific priors used see Armero et al. (2008) where a similar analysis is done.
[11]URL:`http://www.maestre-ediban.com`.

case of the Spanish banking industry, the studies by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011) have considered a relatively large number of socioeconomic variables. However, these studies partly have a geographical bias in the sense that they include only municipalities with more than 1,000 inhabitants which, as shown in Section 3, account for less than 70% of the Spanish territory. Therefore, extending the sample to these municipalities is beneficial, since conclusions will be much more accurate (especially from a *geographical* point of view), and will be applicable also to the population living in remote locations, which may be relevant from a financial exclusion perspective. Although this comes at the price of dropping some of the variables which are considered in the studies by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011), the number of municipalities included in the study increases substantially, comprising *all* Spanish municipalities and, therefore, the entire Spanish territory—no-one is *excluded*. In addition, although in comparison with the studies by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011) our list of likely determinants is shorter, compared with most other studies dealing with similar issues in different banking systems, the set of explanatory factors is similar.

The set of covariates considered in Section 4 contains some of the most frequently considered determinants of bank branch location in the literature. Among them, the inclusion of per capita income is usually considered, but this information is not available for all municipalities and sample years. Alternatively, we will use unemployment, which is negatively correlated with per capita income. The density of population has been considered, for instance, by Evanoff (1988) and, previously, by Lanzillotti and Saving (1969) and Seaver and Fraser (1979). In the context of Spanish banking, it has been included both by Bernad et al. (2008) and Alamá and Tortosa-Ausina (2011). As indicated by Bernad et al. (2008), the rationale would suggest that an increase in population density would reduce the number of branches through the effect of accessibility costs on the demand for banking services. In the particular case we are dealing with, the results can be strongly affected by the different sample we are using, since many of the municipalities included in our sample have a low population density.

The third of the selected covariates corresponds to the percentage of the foreign population. However, the number of authors who have used this type of information are fewer, since it is generally unavailable for many countries. One of the (few) exceptions is Joassart-Marcelli and Stephens (2010), who build on the literature on financial exclusion and ecology to investigate the spatial relationships between immigrant settlement patterns in Greater Boston in 2000 and accessibility to various types of financial institutions. In our particular case, the expected effects may not be entirely clear. In addition, the foreign population may be very different in terms of wealth.[12]

6. Results

The analysis performed in this section has been carried out for all banking firms jointly, and for the different types of banks in the Spanish banking sector (commercial banks, savings banks and credit unions) separately. We have followed this strategy for reasons related to the different implications this might have on financial exclusion (*under-branching*), or the fact that the savings bank sector is the only one which is being profoundly restructured now (*over-branching*). In addition, in the separate analysis, we will also consider the number of branches of the other types of banks as additional covariates to those listed in previous sections in order to test for different industrial organization theories. Specifically, we can test for both *rational herding* (Chang et al., 1997) and/or *rival precedence* (Hannan and McDowell, 1987).

Several contributions have dealt with bank branching patterns and competition issues in Spain, questions which lie beyond the objectives of our article. However, there are some related hypotheses we will partly deal with. For instance, Chang et al. (1997) have empirically explored whether the apparent clustering of bank branches in New York City between July, 1990 and June, 1995 could be at least partially attributed to "rational herding" by banks, which refers to situations where it is individually rational for agents/firms to mimic the actions of others even though such mimicry can potentially lead to aggregate outcomes that are suboptimal. In the case of bank branching patterns in Spain, this type of behavior might have also existed—since the number of total branches has increased proportionally higher than the GDP, especially in the case of savings banks. Therefore, in our particular setting we would consider that the presence of other types of financial institutions might influence the location of the other types, i.e. once savings banks were allowed to establish branches freely, some institutions might have decided to locate where other financial institutions had been established for years.

There are other hypotheses related to the one referred to in the previous paragraph that could also be plausible, including "rival precedence". In the particular case of banking, the underpinnings of this hypothesis are explained in Hannan and McDowell (1987), who found that the adoption of automatic teller machines by rivals increased the conditional probability

[12]Other information considered in the literature that can affect bank branch location are related to economic activity in general, and can be decomposed into different variables such as tourism, commercial activities (both retail and wholesale), number of trucks, etc. However, in the particular case of Spain we are dealing with, this information is missing for municipalities with fewer than 1,000 inhabitants.

that a banking firm adopted such an innovation. This hypothesis is strongly linked to the one referred to above, and we will also test for it.

6.1. Total number of bank branches

According to the methodologies presented in Section 4, our first aim is to analyze the *geographical* effects in our data in order to determine which model fits them better. After testing for different models using DIC, we find that the same pattern holds for both years 2004 and 2008. This is very apparent looking at Tables 4 and 5. For these two years, a *fixed effect per province* is preferred to explain the geographical variation in the number of bank branches per municipality, since these are the models for which the *lowest* values of DIC are found. Therefore, the final selected model for $\log(\lambda_i)$ is

$$\log(\lambda_i) = \alpha_0 + \alpha_1 \log(DENSITY_i) + \alpha_2 UNEMPLOY_i + \alpha_3 FOREIGN_i \quad (8)$$

$$+\beta_1 PROV1_i + \cdots + \beta_{51} PROV51_i + U_i \quad (9)$$

with $U_i \sim N(0, \sigma^2)$ for $i = 1, \ldots, 8109$. Notice that, as mentioned above, we will just consider 51 provincial effects leaving the remaining one as the base province. In particular we consider Burgos as the base province as it has the highest number of municipalities—and hence of observations. We employ MCMC methods for obtaining realizations of the posterior distributions for all the parameters.

Here we present a summary of these realizations of the posterior distributions for $\boldsymbol{\alpha}$ and the standard deviation of the independent random effects, σ_U. This summary contains the mean, the standard deviation, the median and a 50% *credible interval*,[13] which is a central interval containing a share of the probability (50% in our case) under the posterior distribution, and differs from the classical confidence intervals.

Results for years 2004 and 2008 are reported in Table 6. Notice that for both years we observe the same pattern: a positive effect for the share of the foreign population, and a negative effect for the population density and rate of unemployment. This can be seen by noticing that the posterior distribution for these parameters concentrates a 50% of the probability around positive or negative values (see the credible intervals in Table 6). The economic implications

[13] From the Bayesian perspective, estimation of parameters can be performed via credibility (or credible) intervals. In contrast with classical confidence intervals, Bayesian credible intervals contain the true but unknown value of the parameter with a given (by the analyst) probability. When using MCMC, these credible intervals can be easily obtained from the resulting MCMC chains.

would suggest that the observed-to-expected ratio of bank branches *increases* with the foreign population, and it *decreases* with the population density and unemployment rate.

We consider that when the *a posteriori* observed-to-expected ratio of bank branches in a given location is higher than one, it corresponds to the phenomenon of *over-branching* referred to in previous sections. Conversely, if it is lower that one it would indicate the existence of *under-branching*—the number of branches are less than those that we would expect according to our model. Since the observed-to-expected ratio of bank branches increases with the percentage of the foreign population in each municipality, it would imply that the higher the foreign population, the higher the probability of over-branching. If we take the existence of a large share of the foreign population as a proxy for relatively higher economic activity—since foreign-born immigrants tend to settle where economic activity is higher—these results might indicate that banking firms, jointly analyzed, might have *overreacted* to this phenomenon, which has been quite remarkable over the last few years, as shown in both Tables 1 and 3.

This result is reasonable, and it is strongly related to the finding that the observed-to-expected ratio of bank branches *decreases* with unemployment, i.e. when there is an imbalance in the labor market, banks tend to behave in an opposite way to that described in the previous paragraph. In this case, if any tendency exists, it is to set up fewer branches than those expected. The sign of this result coincides with previous findings. What had not been measured so far in the previous literature is the magnitude of the effect, i.e. whether the number of bank branches is either *too high* (or *too low*) with respect to what we should find according to our model of bank branching.

The random effect per municipality, reflected by parameter σ_U, is the standard deviation of the distribution of the random effects per municipality. The value of this parameter can be translated in that the value of λ_i for a specific municipality can be at most 1.3 times the value of this parameter in another municipality. Recall that this parameter is assuming the variability that cannot be explained by means of the covariates. The results hold for both 2004 and 2008, as shown in Table 6.

Finally, the geographical effect is reported in the maps in Figure 3, which show the *mean* per province of the observed-to-expeted ratio of the total number of bank branches, namely, the mean of the λ_i's of all the municipalities in each province, for both sample years. This effect, however, does not only contain the geographical effect but also the effect of the covariates as well as the random effect per municipality, in order to provide a fuller summary of results. The areas in darker colors correspond to the phenomenon of over-branching, whereas those areas in lighter colors correspond to under-branching. It can be observed that over-branching has decreased slightly comparing 2008 and 2004 for some provinces. Although two years (which in addition are relatively close) are not enough for drawing sensible conclusions in terms of dynamics or possible tendencies, it could indicate that the phenomenon of over-branching might have started its retreat when the financial crisis began in Spain.

6.2. Number of commercial bank branches

As indicated in the initial paragraphs of the study, analyzing commercial banks, savings banks and credit unions separately may be important because of the different implications, especially in terms of financial exclusion/inclusion, and because their policies in terms of setting up new branches have differed considerably since complete deregulation took place in 1989. In the case of commercial banks, we will analyze their particular behavior using the model:

$$\begin{aligned} \log(\lambda_i) &= \alpha_0 + \alpha_1 \log(DENSITY_i) + \alpha_2 UNEMPLOY_i + \alpha_3 FOREIGN_i \qquad (10) \\ &+ \alpha_4 SAVINGS_i + \alpha_5 UNIONS_i + \beta_1 PROV1_i + \cdots + \beta_{51} PROV51_i + U_i, \qquad (11) \end{aligned}$$

where the number of saving bank branches ($SAVINGS$) and credit union branches ($UNIONS$) are also considered as covariates. In Table 7 we can observe that the effects of the covariates are similar for both years considered—although the magnitudes of the coefficients vary slightly. Interestingly, population density ($DENSITY$) seems to have the opposite behavior for the commercial banks compared with the general number of bank branches, suggesting that a separate analysis taking into account the different types of firms might indeed be appropriate. Our findings suggest that commercial banks tend to over-branch in those municipalities where population density is higher, which are usually locations where bank competition is tighter. This finding could be related to those by Jayaratne and Strahan (1996), who observed improvements in loan quality but no consistent increase in lending after branch reform. In our case, an excess of bank branches in a given location might indicate the existence of competition in *quality*. In contrast, both the variables $UNEMPLOY$ and $FOREIGN$ have the same sign as those found for all banking firms. These trends hold for both years, although they are stronger for $UNEMPLOY$ in 2004, and for $FOREIGN$ in 2008. This would imply that financial exclusion might be exacerbated over time because of commercial bank branching policies.

Also notice that the number of credit union branches and savings bank branches have a positive correlation with the number of commercial bank branches, as may reasonably be expected in the case that the "rational herding" and "rival precedence" hypotheses hold. The value of the corresponding parameters is small, although this is due to the magnitude of the variable and has nothing to do with this value being close to 0. The σ_U parameter also differs for that found for all banking firms. Its higher value for both years ($\sigma_U^{2004} = 0.1583$ and $\sigma_U^{2008} = 0.1501$), would indicate that the differences across municipalities in the case of commercial banks are larger than when considering all financial institutions.

In the maps in Figure 4 we cannot observe remarkable changes between 2004 and 2008, apart from some movements among provinces. However, we can observe remarkable differences when comparing these maps to those in Figure 3, since for commercial banks the "dark blue" color, which indicates observed-to-expected bank branch ratios higher than unity, vanishes almost entirely, and the white color predominates. This is especially evident in the year 2008, as shown in the lower panel of Figure 4. This implies that in the case of commercial banks, for several provinces the effect that has predominated is under-branching and, therefore, we might conclude these are not the firms contributing to eradicate financial exclusion. In addition, if any tendency exists, it would point towards contributing *less* to financial inclusion, as some provinces move down in their observed-to-expected ratios—as shown by clearer colors—when comparing the maps corresponding to 2004 and 2008.

6.3. Number of savings banks and credit union branches

For the number of savings bank branches in each municipality we consider a slight variation of the models presented above, namely:

$$\begin{aligned}
\log(\lambda_i) &= \alpha_0 + \alpha_1 \log(DENSITY_i) + \alpha_2 UNEMPLOY_i + \alpha_3 FOREIGN_i && (12)\\
&+ \alpha_4 COMMERCIAL_i + \alpha_5 UNIONS_i + \beta_1 PROV1_i + \cdots + \beta_{51} PROV51_i && (13)\\
&+ U_i, && (14)
\end{aligned}$$

In this case, the variables which reflect the existence of rival precedence, or rational herding, would be the number of commercial bank branches ($COMMERCIAL$) and credit union branches ($UNIONS$) in each municipality. In the case of credit unions the model will be only slightly modified, and its expression is as follows:

$$\begin{aligned}
\log(\lambda_i) &= \alpha_0 + \alpha_1 \log(DENSITY_i) + \alpha_2 UNEMPLOY_i + \alpha_3 FOREIGN_i && (15)\\
&+ \alpha_4 SAVINGS_i + \alpha_5 COMMERCIAL_i + \beta_1 PROV1_i + \cdots + \beta_{51} PROV51_i + U_i && (16)
\end{aligned}$$

in which, with respect to models (10) and (12) we are including covariates with the number of commercial banks ($COMMERCIAL$) and savings banks ($SAVINGS$).

Results are reported in Table 8 in the case of savings banks, and Table 9, in the case of credit unions. In both cases, results do not mimic entirely those found for commercial banks. For instance, in the case of population density ($DENSITY$) the sign is just the opposite with respect to that found for commercial banks, and this occurs for both savings banks (Table 8) and credit unions (Table 9). In both cases, this effect is clearly negative as the credible interval indicates. Therefore, for these financial institutions, the lower the density (in terms of population per square kilometer), the higher the observed-to-expected ratio of bank branches, i.e. the possibility of over-branching. This would corroborate the stronger commitment of this type of financial institutions to rural areas (especially in the case of credit unions), or communities living in more isolated locations, for which access to bank services is more difficult (especially in the case of savings banks). In contrast, $UNEMPLOY$ has the same sign. In this case we would find that even though credit unions tend to concentrate in rural areas, they will be discouraged by the fact that the economic conditions in the target area might be difficult. This result is also consistent with the specialization of this type of firms, whose main objective is to provide financial aid to their members.

Finally, the share of foreign population presents a different pattern not only for savings banks and credit unions, but also for the different time periods in the case of the latter group of firms. Credit unions have the opposite behavior with respect to commercial banks, as the probability of over-branching *decreases* with the percentage of foreign population. However, in the case of savings banks this only happens in 2004, whereas in 2008 the behavior is similar to that of commercial banks, although with a much lower coefficient. The positive effect found for the year 2008 would imply that the higher the foreign population in a given location, the higher the observed-to-expected ratio of savings bank branches, whereas this trend was opposite in 2004. Therefore, over time, the behavior of savings banks, at least in some respects, *converges* slightly to that of commercial banks. Although the explanations for this finding may be multiple, it could be the case that savings banks' territorial expansion policies led to an overreaction (over-branching) to the surge in economic activity in some particular areas—as proxied by the settling of foreign-born immigrants.

Also in 2004 the number of commercial banks ($COMMERCIAL$) seemed to have a *sliqhtly* positive effect on the number of savings banks (Table 8), although the effect on credit unions seemed not to have any affect at all—the posterior mean for the coefficient is zero. However, in

2008 the effect of the number of commercial banks on savings banks and credit unions has the opposite effect—i.e. no effect for savings banks and slightly positive effect for credit unions. The positive effects, especially in the case of savings banks, could be due to the fact that, over time, these firms have been providing their customers with financial products and services increasingly similar to what commercial banks were already providing and, therefore, their geographical expansion policies tend also to be more similar to those of commercial banks—i.e., not conditioned by the natural markets in which they had been traditionally established (Illueca et al., 2009, 2008).

Analyzing the effects of the presence of credit union branches ($UNIONS$) on savings banks (Table 8) and vice-versa ($SAVINGS$ in Table 9) is slightly more involved, since savings banks and credit unions do not compete as vigorously as savings banks and commercial banks do. Credit unions have not usually expanded into territories other than their territories of origin, and have a much stronger specialization, especially in the agricultural sector. The strongest result is reported in Table 9, which indicates that the impact of $SAVINGS$ on the probability of over-branching in the case of credit unions is negative corroborating that this firms cannot be considered as strong competitors. This could also indicate that savings banks and credit unions have a substitutive effect—if a credit union has a branch in a given area or municipality, savings banks might be discouraged to enter that particular market. In contrast, the zero valued effect found for commercial banks would indicate that this type of banks and credit unions emphasize different lines of business, i.e. have different specializations.

The σ_U parameter differs strongly in both dimensions, i.e. between savings banks and credit unions, and over time for both types of firms. They also differ with respect to that obtained for commercial banks. It is especially higher for credit unions (Table 9), where the effect doubles that found for savings banks (Table 8), in both 2004 and 2008, and almost doubles that found for commercial banks. This would indicate that the patterns found vary strongly across municipalities for credit unions, but less for savings banks, indicating that the geographic expansion of these firms has been partly homogeneous throughout the Spanish territory.

In Figure 5 we observe a slight decline in the degree of *over-branching*. This decline could suggest that, by 2008, the year in which the financial crisis started in Spain, savings banks were starting to re-define their territorial expansion policies. This issue deserves further examination, since the policies promoting a restructuring of the savings banks' sector as just starting to being implemented. However, there is an issue which cannot be neglected, namely, the higher over-branching of savings banks compared to that of commercial banks (see Figure 4), for which the dominating trend was the opposite, as indicated above. In contrast, in Figure 6 we observe that credit unions tend to over-branch much more than the rest of the financial institutions aggregates, and this occurs both in 2004 and 2008, but remarkable differences across the Spanish territory are present.

7. Conclusions

This article has analyzed the geography of bank branch location in Europe and, in particular, in Spain in the 2000s from a Bayesian perspective. The study is of particular interest for a variety of reasons. Among them, we should highlight the fact that the current international financial crisis is affecting strongly the Spanish banking system, whose implications should not be neglected because it is the fifth largest bank system in Europe.

Analyzing the geography of Spanish banking is also relevant because there is a diverse range of ownership types, including commercial banks, savings banks, cooperative banks, and specialized credit institutions, and their performance has differed remarkably since the financial crisis started. Specifically, savings banks, which are even larger than commercial banks in dimensions as important as the number of branches, are being especially affected due to their high level of involvement in funding the construction boom of the 2000s and, related to this, the aggressive geographical expansion policies some of these institutions had started since they were allowed to do so in 1989. This deregulatory initiative bears several similarities to that which occurred in the US due to the passing of the Riegle-Neal Act in 1994.

These expansion policies are now put into question and, as a matter of fact, the number of savings bank branches has decreased sharply between 2008 and 2010, and it is forecast to decrease more sharply in the next few years (implying that excess capacity might be taking place), partly due to the restructuring of the sector which will ultimately transform them into banks—as advised, twenty years ago, by Revell (1989). Therefore, the Spanish banking sector is *a priori* an interesting setting in which to analyze different issues related to the geography of bank branching.

This topic is related to the literature on branch banking and service availability and, to a lesser extent, to the literature on financial exclusion. Although both literatures, which are closely related, are relevant, the number of studies is low, although some recent ones (Bernad et al., 2008; Alamá and Tortosa-Ausina, 2011) have been focusing on the Spanish banking sector. However, the available evidence has not dealt explicitly with two relevant issues: (i) considering the entire *geography* of Spanish banking (in Spain, municipalities with a population under 5,000 represent more than 70% of occupied land); and (ii) explicitly addressing the issue as to to whether financial institutions might be either under- or over-branching, which the Bayesian techniques used in this paper enable. Both phenomena are relevant, and both are related to important literature. The first one, i.e. under-branching, is related to the literature referred to on financial exclusion, whereas over-branching has strong links with the literature on excess capacity in banking, a phenomenon which is now affecting the Spanish banking system.

Results can be explored from a variety of angles. Among them, we should highlight that, indeed, there was a substantial amount of both over- and under-branching, although with different actors involved. According to our models of bank branch location, which explicitly consider different covariates that the literature has been taking into account, along with a geographical and a random effect per municipality component, both savings banks and credit unions have been contributing to limit financial exclusion. However, savings banks are now allowed to set up branches throughout the Spanish territory, which has contributed to the phenomenon of over-branching. This excess of capacity, a well-known problem in the banking sector in general, has led to a deep restructuring in the sector of savings banks and, in the close future, in the sector of credit unions. It is therefore an open research question to evaluate further whether this phenomenon might jeopardize the future financial inclusion of unfavored local communities.

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References

Alamá, L. and Tortosa-Ausina, E. (2011). Bank branch geographic location patterns in Spain: some implications for financial exclusion. Working Paper-EC Series 2011-10, Ivie, València.

Amable, B., Chatelain, J.B., and De Bandt, O. (2002). Optimal capacity in the banking sector and economic growth. *Journal of Banking and Finance*, **26**(2): p. 491–517.

Armero, C., López-Quílez, A., and López-Sánchez, R. (2008). Bayesian assessment of times to diagnosis in breast cancer screening. *Journal of Applied Statistics*, **35**(9): p. 997–1009.

Banerjee, S., Carlin, B.P., and Gelfand, A.E. (2004). *Hierarchical Modeling and Analysis for Spatial Data*. Chapman and Hall/CRC.

Berger, A.N. and DeYoung, R. (2001). The effects of geographic expansion on bank efficiency. *Journal of Financial Services Research*, **19**(2–3): p. 163–184.

Berger, A.N., Kashyap, A.K., and Scalise, J.M. (1995). The transformation of the U.S. banking industry: What a long, strange trip it's been. *Brookings Papers on Economic Activity*, **2**: p. 55–218.

Berger, J.O. (2006). The Case for Objective Bayesian Analysis. *Bayesian Analysis*, **1**(3): p. 385–402.

Bernad, C., Fuentelsaz, L., and Gómez, J. (2008). Deregulation and its long-run effects on the availability of banking services in low-income communities. *Environment and Planning A*, **40**(7): p. 1681–1696.

Besag, J. (1974). Spatial Interaction and the Statistical Analysis of Lattice Systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, **36**(2): p. 192–236.

Bikker, J.A., Groeneveld, J.M., and Bank, N. (2000). Competition and concentration in the EU banking industry. *Kredit und Kapital*, **33**(1): p. 62–98.

Carbó, S., Gardener, E.P.M., and Molyneux, P. (2005). *Financial Exclusion*. Palgrave MacMillan.

Carbó, S., Gardener, E.P.M., and Molyneux, P. (2007). Financial exclusion in Europe. *Public Money and Management*, **27**(1): p. 21–27.

Chang, A., Chaudhuri, S., and Jayaratne, J. (1997). Rational herding and the spatial clustering of bank branches: an empirical analysis. Research Paper 9724, Federal Reserve Bank of New York, New York, NY.

Degryse, H. and Ongena, S. (2005). Distance, lending relationships, and competition. *The Journal of Finance*, **60**(1): p. 231–266.

DeYoung, R., Klier, T., and McMillen, D.P. (2004). The changing geography of the U.S. banking industry. *The Industrial Geographer*, **2**(1): p. 29–48.

Dymski, G.A. and Veitch, J.M. (1996). Financial transformation and the metropolis: booms, busts, and banking in Los Angeles. *Environment and Planning A*, **28**: p. 1233–1260.

Evanoff, D.D. (1988). Branch banking and service accessibility. *Journal of Money, Credit and Banking*, **20**(2): p. 191–202.

Gammerman, D. and Lopes, H. (2006). *Monte Carlo Markov Chain: Stochastic Simulation for Bayesian Inference*. Chapman and Hall, 2nd edition.

Garrett, T.A., Wagner, G.A., and Wheelock, D.C. (2005). A spatial analysis of state banking regulation. *Papers in Regional Science*, **84**(4): p. 575–595.

Gilbert, G. and Longbrake, W. (1973). The effects of branching by financial institutions on competition, productive efficiency and stability. *Journal of Bank Research*, **4**: p. 154–167.

Gilbert, G.G. (1974). Predicting de novo expansion in bank merger cases. *Journal of Finance*, **29**(1): p. 151–162.

Goldstein, M. (2006). Subjective Bayesian Analysis: Principles and Practice. *Bayesian Analysis*, **1**(3): p. 403–420.

Green, P.J. (2001). *Complex Stochastic System*, chapter A Primer on Markov Chain Monte Carlo, p. 1–62. Chapman and Hall/CRC.

Hannan, T.H. and McDowell, J.M. (1987). Rival precedence and the dynamics of technology adoption: an empirical analysis. *Economica*, **54**: p. 155–171.

Huang, R. (2007). Evaluating the real effect of bank branching deregulation: Comparing contiguous counties across US state borders. *Journal of Financial Economics*, **87**: p. 678–705.

Illueca, M., Norden, L., and Udell, G.F. (2008). Liberalization, corporate governance, and savings banks. EFA 2008 Athens Meetings Paper.

Illueca, M., Pastor, J.M., and Tortosa-Ausina, E. (2009). The effects of geographic expansion on the productivity of Spanish savings banks. *Journal of Productivity Analysis*, **32**(2): pp. 119–143.

Jacobs, D.P. (1965). The Interaction Effects of Restrictions on Branching and Other Bank Regulations. *The Journal of Finance*, **20**(2): p. 332–348.

Jayaratne, J. and Strahan, P.E. (1996). The Finance-Growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, **111**(3): p. 639–670.

Joassart-Marcelli, P. and Stephens, P. (2010). Immigrant banking and financial exclusion in Greater Boston. *Journal of Economic Geography*, **10**(6): p. 883–912.

Lanzillotti, R.F. and Saving, T.R. (1969). State Branching Restrictions and the Availability of Branching Services: Comment. *Journal of Money, Credit and Banking*, **1**(4): p. 778–788.

Leyshon, A. and Thrift, N. (1995). Geographies of financial exclusion: financial abandonment in Britain and the United States. *Transactions of the Institute of British Geographers, New Series*, **20**: p. 312–341.

Leyshon, A. and Thrift, N. (1996). Financial exclusion and the shifting boundaries of the financial system. *Environment and Planning A*, **28**(7): p. 1150–1156.

Marshall, J.N. (2004). Financial institutions in disadvantaged areas: a comparative analysis of policies encouraging financial inclusion in Britain and the United States. *Environment and Planning A*, **36**(2): p. 241–261.

McCulloch, R.E. and Searle, S.R. (2001). *Generalized, Linear, and Mixed Models.* John Wiley and Sons.

Okeahalam, C. (2009). Bank Branch Location: a Count Analysis. *Spatial Economic Analysis*, **4**(3): p. 275–300.

Pollard, J.S. (1996). Banking at the margins: a geography of financial exclusion in Los Angeles. *Environment and Planning A*, **28**: p. 1209–1232.

Revell, J. (1989). The future of savings banks: A study of Spain and the rest of Europe. Research Monographs in Banking and Finance 8, Institute of European Finance, Bangor, UK.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, **6**(2): pp. 461–464.

Seaver, W.L. and Fraser, D.R. (1979). Branch banking and the availability of banking services in metropolitan areas. *Journal of Financial and Quantitative Analysis*, **14**(1): p. 153–160.

Shaffer, S. (1996). Viability of traditional banking activities: evidence from shifts in conduct and excess capacity. *International Journal of the Economics of Business*, **3**(2): p. 125–143.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., and van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society. Series B*, **64**(4): pp. 583–639.

Spiegelhalter, D.J., Thomas, A., Best, N., and Lunn, D. (2003). *WinBUGS version (1.4)*. MRC Biostatistics Unit, Cambridge, UK.

Zhao, Y., Staudenmayer, J., Coull, B., and Wand, M. (2006). General design Bayesian generalized linear mixed models. *Statistical Science*, **21**(1): pp. 35–51.

Table 1: Number of branches in the Spanish banking sector by type of institution

Year	Total		Commercial banks			Savings banks			Credit unions		
	Number	% change	Number	% change	Share	Number	% change	Share	Number	% change	Share
1986	30,961		16,518			11,061			3,382		
1987	31,500	1.7	16,498	–0.1	52.4	11,754	6.3	37.3	3,248	–4.0	10.3
1988	31,972	1.5	16,691	1.2	52.2	12,252	4.2	38.3	3,029	–6.7	9.5
1989	32,735	2.4	16,677	–0.1	50.9	13,168	7.5	40.2	2,890	–4.6	8.8
1990	33,478	2.3	16,917	1.4	50.5	13,642	3.6	40.7	2,919	1.0	8.7
1991	34,873	4.2	17,824	5.4	51.1	14,031	2.9	40.2	3,018	3.4	8.7
1992	35,429	1.6	18,058	1.3	51.0	14,291	1.9	40.3	3,080	2.1	8.7
1993	35,193	–0.7	17,636	–2.3	50.1	14,485	1.4	41.2	3,072	–0.3	8.7
1994	35,544	1.0	17,557	–0.4	49.4	14,880	2.7	41.9	3,107	1.1	8.7
1995	36,251	2.0	17,842	1.6	49.2	15,214	2.2	42.0	3,195	2.8	8.8
1996	37,079	2.3	17,674	–0.9	47.7	16,094	5.8	43.4	3,311	3.6	8.9
1997	37,634	1.5	17,530	–0.8	46.6	16,636	3.4	44.2	3,468	4.7	9.2
1998	38,639	2.7	17,450	–0.5	45.2	17,582	5.7	45.5	3,607	4.0	9.3
1999	38,986	0.9	16,905	–3.1	43.4	18,337	4.3	47.0	3,744	3.8	9.6
2000	38,967	0.0	15,811	–6.5	40.6	19,268	5.1	49.4	3,888	3.8	10.0
2001	38,676	–0.7	14,756	–6.7	38.2	19,829	2.9	51.3	4,091	5.2	10.6
2002	38,673	0.0	14,072	–4.6	36.4	20,326	2.5	52.6	4,275	4.5	11.1
2003	39,405	1.9	14,074	0.0	35.7	20,871	2.7	53.0	4,460	4.3	11.3
2004	40,230	2.1	14,168	0.7	35.2	21,503	3.0	53.5	4,559	2.2	11.3
2005	41,599	3.4	14,533	2.6	34.9	22,410	4.2	53.9	4,656	2.1	11.2
2006	43,286	4.1	15,096	3.9	34.9	23,418	4.5	54.1	4,772	2.5	11.0
2007	45,086	4.2	15,542	3.0	34.5	24,591	5.0	54.5	4,953	3.8	11.0
2008	45,662	1.3	15,580	0.2	34.1	24,985	1.6	54.7	5,097	2.9	11.2
2009	44,085	–3.5	14,840	–4.7	33.7	24,202	–3.1	54.9	5,043	–1.1	11.4
2010	42,894	–2.7	15,227	2.6	35.5	22,649	–6.4	52.8	5,018	–0.5	11.7
Average change 1986–1999		1.66		0.17			3.68			0.73	
Average change 1999–2008		1.77		–0.90			3.50			3.49	
Average change 2008–2010		–3.08		–1.14			–4.79			–0.78	
Average change 1986–2008		1.78		–0.27			3.77			1.88	
Average change 1986–2010		1.37		–0.34			3.03			1.66	

Source: Bank of Spain and own elaboration.

Table 2: Distribution of bank branches according to municipalities' population size, 2008

Size of the municipality (population)	Number of municipalities	Cumulated population	Percentage of population	Cumulated land occupied	Percentage of land occupied	Percentage of commercial banks' branches	Percentage of savings banks' branches	Percentage of credit unions' branches
<1,000	4,858	1,508,949	3.27	192,351.63	38.12	0.81	5.09	12.05
1,000–5,000	1,961	4,540,905	9.84	159,504.84	31.61	9.74	11.45	21.51
5,000–20,000	906	8,855,578	19.19	89,824.34	17.80	21.41	15.42	18.43
20,000–50,000	239	6,997,338	15.16	34,784.06	6.89	13.46	13.53	12.05
50,000–100,000	84	5,848,264	12.67	14,122.57	2.80	11.89	12.40	8.51
>100,000	61	18,401,641	39.87	13,952.72	2.77	42.69	42.11	27.44
Total	8,109	46,152,675	100.00	504,540.16	100.00	100.00	100.00	100.00

Sources: Bank of Spain, Instituto Nacional de Estadística and Guía de la Banca (ed. Maestre Edibán).

Table 3: Basic data by province (NUTS 3), years 2004 and 2008

Province	Unemployment (number of people)		Population (number of people)		Immigrant population (number of people)		Number of commercial banks' branches		Number of savings banks' branches		Number of credit unions' branches	
	2004	2008	2004	2008	2004	2008	2004	2008	2004	2008	2004	2008
Álava/Araba	9,493	18,219	295,905	309,635	12,058	22,840	110	135	132	167	62	72
Albacete	20,062	36,733	379,448	397,493	16,065	31,128	97	108	160	185	76	83
Alicante/Alacant	53,470	175,969	1,657,040	1,891,477	260,316	446,368	643	765	691	881	191	215
Almería	13,877	56,499	580,077	667,635	66,181	131,330	166	207	248	347	201	186
Ávila	6,106	12,249	166,108	171,815	4,448	11,782	527	72	306	135	104	19
Badajoz	44,180	72,423	663,896	685,246	8,600	21,569	61	333	119	347	12	140
Balears (Illes)	34,072	44,792	955,045	1,072,844	131,423	223,036	327	736	281	657	125	31
Barcelona	161,656	373,364	5,117,885	5,416,447	469,236	745,216	584	1,932	571	4,079	27	94
Burgos	12,523	22,934	356,437	373,672	13,331	32,073	1,790	159	3,667	362	98	77
Cáceres	21,896	63,831	411,390	412,498	11,466	13,746	140	171	335	338	70	21
Cádiz	80,807	157,370	1,164,374	1,220,467	21,409	42,804	252	307	236	464	9	62
Castellón/Castelló	11,408	47,071	527,345	594,915	52,247	106,125	218	239	227	293	173	190
Ciudad Real	25,424	45,583	492,914	522,343	16,945	41,396	11	135	12	265	2	110
Córdoba	40,501	72,609	779,870	798,822	10,303	21,937	122	233	239	396	101	109
Coruña (A)	64,979	82,588	1,121,344	1,139,121	19,945	33,711	563	628	392	459	3	4
Cuenca	6,895	14,270	204,546	215,274	10,325	24,348	74	75	100	108	85	90
Girona	15,887	46,925	636,198	731,864	79,133	149,236	167	340	320	556	14	5
Granada	35,722	76,762	841,687	901,220	26,876	58,775	257	221	374	441	54	188
Guadalajara	5,497	16,708	193,913	237,787	13,504	34,310	201	78	357	191	101	21
Guipúzcoa/Gipuzkoa	21,436	36,347	686,513	701,056	18,232	35,935	318	333	494	231	2	118
Huelva	17,987	43,709	476,707	507,915	14,428	37,110	192	141	369	251	163	87
Huesca	4,346	11,146	212,901	225,271	11,905	24,363	60	109	148	165	23	75
Jaén	22,359	47,943	654,458	667,438	8,745	18,572	297	164	184	371	104	144
León	19,592	34,171	492,720	500,200	11,577	23,380	117	278	210	290	82	30
Lleida	7,326	22,839	385,092	426,872	31,370	69,366	101	200	158	390	71	18
La Rioja	8,039	20,113	293,553	317,501	24,988	43,856	157	160	346	316	131	58
Lugo	16,850	19,871	358,452	355,549	5,542	11,582	130	210	275	133	43	34
Madrid	203,824	405,150	5,804,829	6,271,638	664,255	1,005,381	236	2,998	226	3,268	17	122
Málaga	58,175	154,947	1,397,925	1,563,261	144,462	250,432	191	563	352	691	15	206
Murcia	36,707	103,089	1,294,694	1,426,109	132,918	201,700	207	446	122	721	34	270
Navarra	17,270	37,939	584,734	620,377	43,376	65,045	2,432	339	2,628	307	85	186
Ourense	18,820	24,351	340,258	336,099	10,283	14,006	12	190	6	214	2	7
Asturias	58,619	74,381	1,073,761	1,080,138	22,429	40,804	374	526	568	375	248	134
Palencia	8,293	11,300	173,990	173,454	2,765	5,998	450	100	503	130	154	26
Palmas (Las)	62,754	131,389	987,128	1,070,032	91,080	142,757	261	366	287	371	168	62
Pontevedra	56,383	83,670	930,931	953,400	22,617	36,269	189	501	210	418	7	3
Salamanca	18,691	27,806	350,984	353,404	8,838	15,355	89	198	120	196	25	85
Santa Cruz de Tenerife	50,626	106,856	928,412	1,004,062	94,701	140,844	299	336	246	338	42	87
Cantabria	23,827	38,382	554,784	582,138	16,364	33,242	428	267	354	265	3	20
Segovia	3,747	8,359	152,640	163,899	9,370	20,451	161	82	167	117	81	32
Sevilla	93,986	183,991	1,792,420	1,875,462	29,166	62,319	297	594	267	847	71	170
Soria	2,213	4,615	91,652	94,646	4,209	8,420	77	57	94	72	31	50
Tarragona	18,220	55,211	674,144	788,895	63,107	139,972	515	251	703	606	152	38
Teruel	3,273	7,350	139,333	146,324	7,428	17,043	53	55	67	121	45	74
Toledo	25,081	59,336	578,060	670,203	32,019	74,826	209	246	544	326	27	163
Valencia/València	86,539	205,817	2,358,919	2,543,209	151,754	294,846	58	1,017	115	1,252	69	489
Valladolid	25,179	37,986	510,863	529,019	14,139	29,674	205	262	256	290	146	109
Vizcaya/Bizkaia	44,542	66,191	1,132,861	1,146,026	28,876	58,555	888	500	1,008	462	424	186
Zamora	9,205	13,150	198,524	197,221	2,623	7,669	214	86	226	123	105	69
Zaragoza	25,603	61,432	897,350	952,445	58,212	113,330	444	347	388	642	148	287
Ceuta	5,333	8,551	74,654	77,389	2,863	3,124	78	12	107	15	65	2
Melilla	4,214	8,651	68,016	71,448	5,874	6,472	323	14	555	8	249	2

Sources: Instituto Nacional de Estadística (INE) and Guía de la Banca (ed. Maestre Edibán).

Table 4: Deviance Information Criterion (DIC) for each geographical effect considered (2004)

Geographical Effect	DIC
No effect	21237.7
Random/community	20,604.1
Random/Province	20,383.4
Fixed/community	20,600.1
Fixed/province	20,375.8
Spatial/community	21,205.0
Spatial/province	20,998.8

The shaded row indicates that the fixed/province model is the preferred since it has the smallest DIC.

Table 5: Deviance Information Criterion (DIC) for each geographical effect considered (2008)

Geographical Effect	DIC
No effect	21,572.7
Random/community	20,966.3
Random/Province	20,850.2
Fixed/community	20,964.8
Fixed/province	20,842.3
Spatial/community	21,506.6
Spatial/province	21,350.4

The shaded row indicates that the fixed/province model is the preferred one since it has the smallest DIC.

Table 6: Main features of the posterior distribution of the regression coefficients $\boldsymbol{\alpha}$ and the variance of the independent random effect (σ_U), all banking firms

Year 2004						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_1	Intercept	0.9050	0.0895	0.8475	0.9100	0.9658
α_2	*DENSITY*	–0.0191	0.0039	–0.0217	–0.0191	–0.0164
α_3	*UNEMPLOY*	–0.0202	0.0096	–0.0268	–0.0203	–0.0136
α_4	*FOREIGN*	0.0055	0.0013	0.0046	0.0055	0.0063
σ_U	sd–municipality	0.1485	0.0085	0.1423	0.1482	0.1540
Year 2008						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	0.8034	0.0644	0.7575	0.8093	0.8489
α_1	*DENSITY*	–0.0126	0.0020	–0.0139	–0.0126	–0.0113
α_2	*UNEMPLOY*	–0.0193	0.0067	–0.0242	–0.0195	–0.0146
α_3	*FOREIGN*	0.0053	0.0009	0.0047	0.0053	0.0060
σ_U	sd-municipality	0.1365	0.0073	0.1316	0.1368	0.1417

Table 7: Main features of the posterior distribution of the regression coefficients $\boldsymbol{\alpha}$ and the variance of the independent random effect σ_U, commercial banks

Year 2004						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	0.0113	0.1605	–0.1009	–0.0006	0.1134
α_1	*DENSITY*	0.0075	0.0051	0.0041	0.0076	0.0111
α_2	*UNEMPLOY*	–0.0159	0.0134	–0.0246	–0.0149	–0.0062
α_3	*FOREIGN*	0.0203	0.0019	0.0190	0.0204	0.0216
α_4	*SAVINGS*	0.0002	0.0001	0.0002	0.0002	0.0003
α_5	*UNIONS*	0.0014	0.0011	0.0006	0.0014	0.0022
σ_U	sd-municipality	0.1583	0.0124	0.1494	0.1580	0.1664
Year 2008						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	0.0145	0.1411	–0.0940	0.0073	0.1188
α_1	*DENSITY*	0.0083	0.0031	0.0065	0.0082	0.0103
α_2	*UNEMPLOY*	–0.0219	0.0129	–0.0310	–0.0229	–0.0129
α_3	*FOREIGN*	0.0149	0.0013	0.0141	0.0149	0.0158
α_4	*SAVINGS*	0.0001	0.0001	0.0001	0.0001	0.0002
α_5	*UNIONS*	0.0020	0.0009	0.0014	0.0020	0.0026
σ_U	sd–municipality	0.1501	0.0138	0.1410	0.1502	0.1589

Table 8: Main features of the posterior distribution of the regression coefficients $\boldsymbol{\alpha}$ and the variance of the independent random effect σ_U, savings banks

Year 2004						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	1.0373	0.1148	0.9576	1.0360	1.1180
α_1	*DENSITY*	–0.0249	0.0052	–0.0285	–0.0249	–0.0214
α_2	*UNEMPLOY*	–0.0148	0.0112	–0.0225	–0.0147	-0.0074
α_3	*FOREIGN*	–0.0013	0.0017	–0.0024	–0.0012	–0.0002
α_4	*COMMERCIAL*	0.0001	0.0001	0.0001	0.0001	0.0002
α_5	*UNIONS*	0.0005	0.0009	–0.0001	0.0005	0.0011
σ_U	sd-municipality	0.1158	0.0095	0.1087	0.1156	0.1222

Year 2008						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	0.8996	0.0961	0.8372	0.8969	0.9694
α_1	*DENSITY*	–0.0163	0.0026	–0.0182	–0.0163	–0.0145
α_2	*UNEMPLOY*	–0.0102	0.0091	–0.0170	–0.0100	–0.0033
α_3	*FOREIGN*	0.0022	0.0011	0.0015	0.0022	0.0029
α_4	*COMMERCIAL*	0.0000	0.0001	–0.0000	0.0000	0.0001
α_5	*UNIONS*	0.0019	0.0007	0.0014	0.0019	0.0024
σ_U	sd-municipality	0.1088	0.0093	0.1028	0.1090	0.1148

Table 9: Main features of the posterior distribution of the regression coefficients $\boldsymbol{\alpha}$ and the variance of the independent random effect σ_U, credit unions

Year 2004						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	1.3138	0.2102	1.1792	1.3265	1.4520
α_1	*DENSITY*	–0.0778	0.0101	–0.0844	–0.0779	–0.0711
α_2	*UNEMPLOY*	–0.0029	0.0218	–0.0184	–0.0012	0.0120
α_3	*FOREIGN*	–0.0168	0.0037	–0.0193	–0.0167	–0.0143
α_4	*SAVINGS*	–0.0005	0.0007	–0.0009	–0.0005	–0.0000
α_5	*COMMERCIAL*	0.0000	0.0008	–0.0005	0.0000	0.0005
σ_U	sd-municipality	0.3085	0.0220	0.2928	0.3083	0.3230
Year 2008						
				Quartile		
Coefficient	Variable	Mean	sd	25%	50%	75%
α_0	Intercept	1.6483	0.2136	1.4902	1.6555	1.7970
α_1	*DENSITY*	–0.0598	0.0055	–0.0635	–0.0596	–0.0558
α_2	*UNEMPLOY*	–0.0324	0.0193	–0.0454	–0.0318	–0.0189
α_3	*FOREIGN*	–0.0125	0.0023	–0.0140	–0.0125	–0.0109
α_4	*SAVINGS*	–0.0006	0.0005	–0.0009	–0.0006	–0.0003
α_5	*COMMERCIAL*	0.0002	0.0005	–0.0001	0.0002	0.0006
σ_U	sd-municipality	0.2393	0.0209	0.2276	0.2410	0.2530

Figure 1: Spanish municipalities (LAU 2) by size, 2008
(in yellow municipalities with population size<1,000)

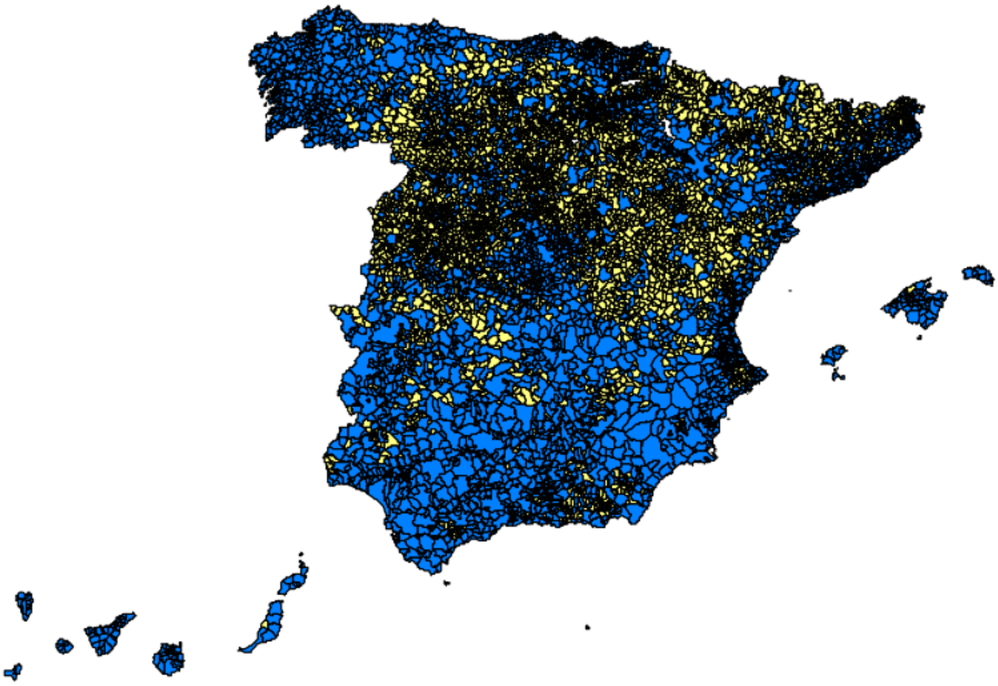


Figure 2: Spanish municipalities (LAU 2) by size, 2008
(in yellow municipalities with population size<1,000)
(in orange municipalities with population between 1,000 and 5,000)

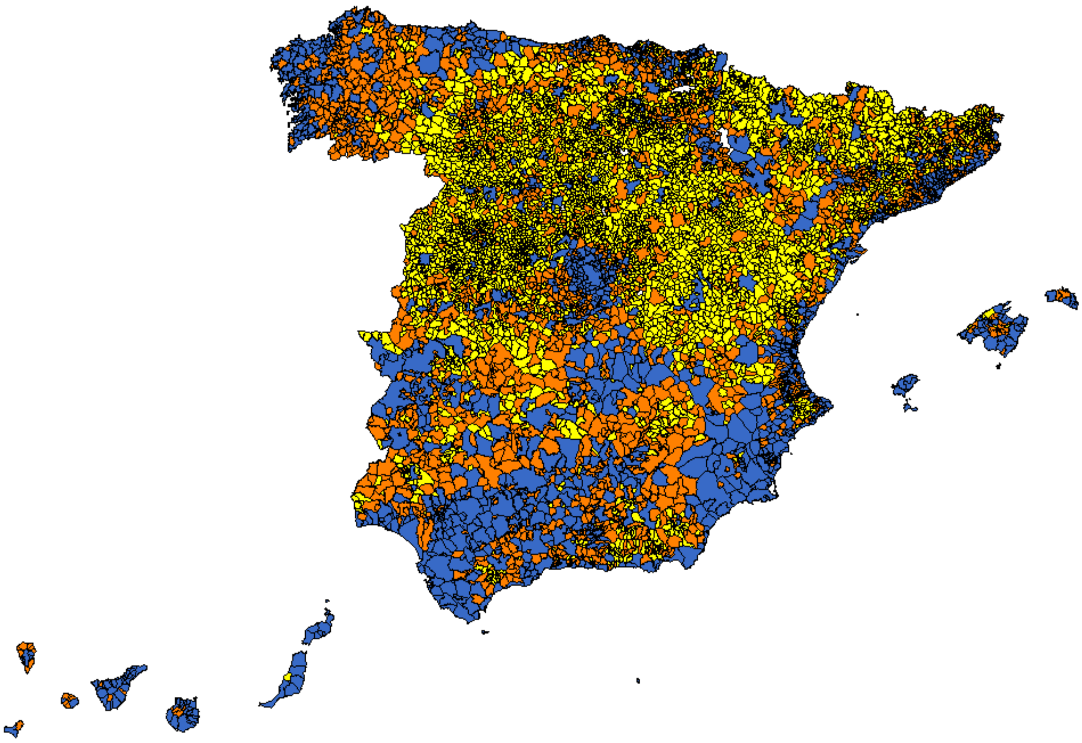
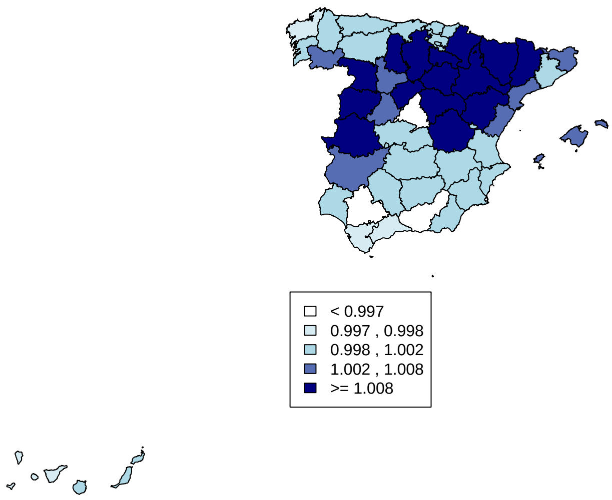


Figure 3: Mean λ_i per province, all banking firms

(a) Year 2004



(b) Year 2008

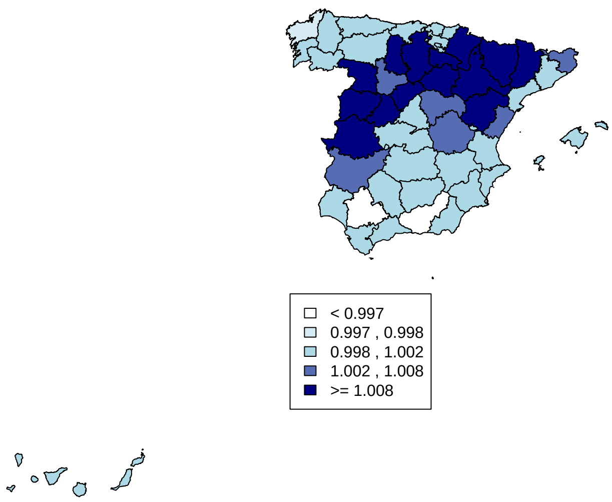
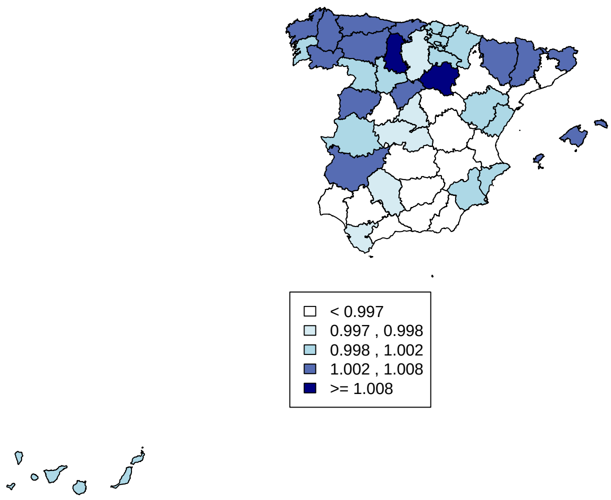


Figure 4: Mean λ_i per province, commercial banks

(a) Year 2004



(b) Year 2008

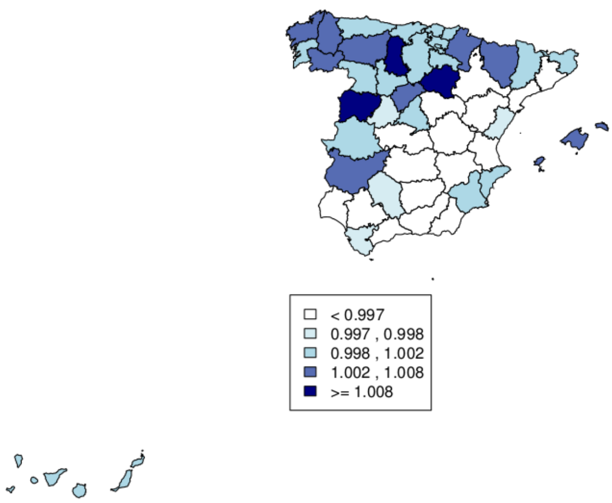
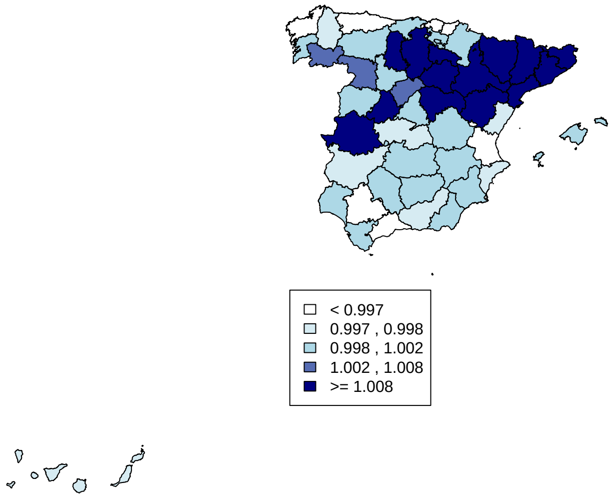


Figure 5: Mean λ_i per province, savings banks

(a) Year 2004



(b) Year 2008

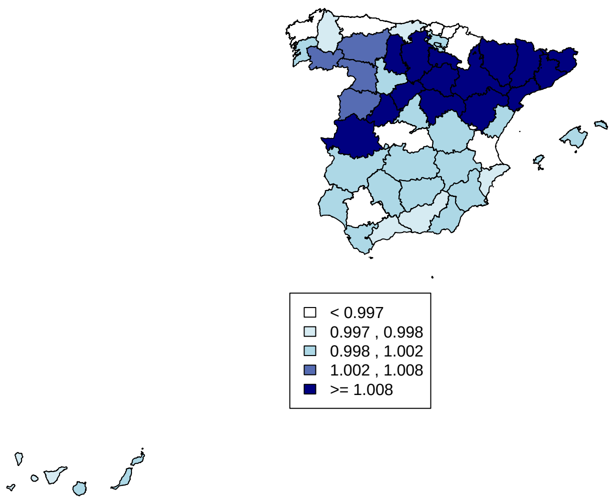
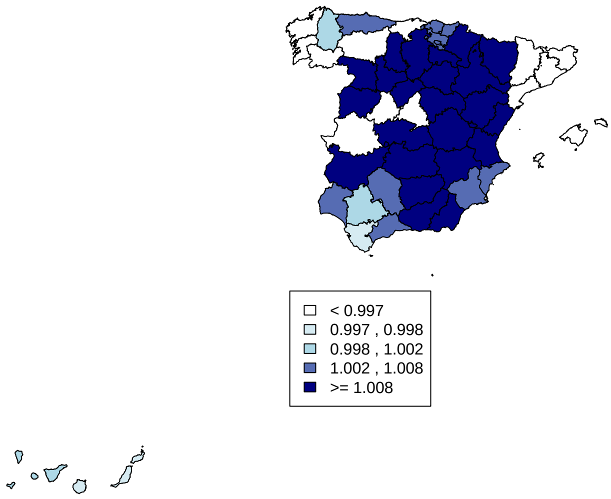


Figure 6: Mean λ_i per province, credit unions

(a) Year 2004



(b) Year 2008