Evolution of the influence of geography on the location of production in Spain (1930-2005)

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3 February 2008

12. Evolution of the influence of geography on the location of production in Spain (1930-2005)[1]

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ABSTRACT

In this paper, we investigate the relative importance of geographic features on the location of production in Spain. Specifically, we want to quantify how much of the spatial pattern of GDP can be attributed to only exogenous *first nature* elements (physical and political geography) and how much can be derived from endogenous *second nature* factors (man-made agglomeration economies). In order to disentangle both effects empirically, and to learn how they are interrelated, we control for second nature. We use a methodology based on an analysis of variance (ANOVA), which is applied to a panel of 47 Spanish provinces in the period 1930-2005. We demonstrate that results can be biased if spatial autocorrelation and spatial heterogeneity, as well as multicollinearity and endogeneity, are not properly taken into account. In the Spanish case, we detect strong spatial heterogeneity in the form of two main clusters. As expected, gross second nature forces are more important than net natural advantages, though their effects range from about 55% in the hinterland to 80% in the coast.

Key-words: Agglomeration, Geography, Spatial Heterogeneity, Endogeneity, Spanish Regions

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[1] Coro Chasco acknowledges financial support from the Spanish Ministry of Education and Science SEJ2006-02328/ECON and SEJ2006-14277-C04-01.

12.1 Introduction

In recent years, there is a growing interest in the geographic aspects of development or the question of where economic activities take place. There is an extensive literature in urban economics, location theory and economic agglomeration. In fact, many economic activities are concentrated geographically and most people in advances countries or regions live in densely populated metropolitan areas. The main issue is how to explain this concentration. Most of the references assume two approaches, *first nature* (Sachs 2000) and *second nature* (Krugman 1993; Krugman 1999; Venables 2003), which are also identified as Sachs' (first nature) and Krugman's approach (second nature). As stated in Roos (2005), real world agglomeration is caused by both first and second nature but it is interesting to compute the exact influence of both types of agglomeration advantages on economic distribution across space.

In this paper, we want to examine the influence of geographic features on the location of production in Spain. In other words, we want to quantify how much of the geographic pattern of GDP can be attributed to only exogenous first nature elements (physical and political geography), how much can be derived from endogenous second nature factors (man-made agglomeration economies) and how much is due to the interaction of both effects. Specifically we disentangle the two net effects empirically, as well as their mixed effect, for the Spanish case analyzing their evolution during the Twentieth Century.

For this purpose, we follow the methodology proposed by Roos (2005) for Germany. He proposes to employ an analysis of variance (ANOVA) to infer the unobservable importance of first nature indirectly in a stepwise procedure. In order to disentangle first and second nature effects empirically, we control for second nature because every locational endowment will be reinforced and overlaid by second nature advantages. In a dynamic context, we also estimate how much of agglomeration can by explained by both gross and net second nature with the aim of isolating the importance of first nature alone.

Whereas this method seems quite clear and direct, we demonstrate that results could be biased if some potential econometric questions are not properly taken into account; e.g. multicollinearity, relevant missing variables, endogeneity, spatial autocorrelation and spatial heterogeneity. In fact, in many countries GDP density is strongly polarized on two subspaces: core and periphery. In the particular case of Spain, the core is located in the coastal plus Madrid provinces and the periphery is constituted by the hinterland. If we consider the Spanish territory as a whole, we find that at most, 88% of GDP's spatial variation can be explained by direct and indirect effects of geography during the Twentieth Century. This result contrast with Roos' findings for Germany (72%) pointing out the main role played by geography in Spain. After controlling for agglomeration economies and the interaction effect of first-second nature, the net influence of natural geography is only about 6-7% nowadays. Nevertheless, some of these results could be significantly biased for the group of inland provinces, in which only a 56% of agglomeration is explained by geography, being the mixed effects the most determining almost along the whole period.

The organization of the Chapter is as follows. In Section 12.2, we describe the state of the art. In particular, we discuss the distinction between first and second nature more deeply and argue that this distinction is theoretically attractive but difficult to measure empirically. Section 12.3 contains a description of the data and the ANOVA model. Section 12.4 analyses the evolution of agglomeration in Spain during the Twentieth Century. The empirical results derived from the econometric process are presented in Section 12.5. The conclusions in Section 12.6 and the references put an end to our analysis.

12.2 Theoretical principles and background

Since it would be impossible to summarize in any simple way the rich range of conclusions from the studies related to this matter, next we highlight some of the most significant for our econometric analysis.

12.2.1 First nature

First nature factors are also called 'pure geography' (Henderson 1999). They are natural features such as climate or resource endowments, which are *exogenous* to the economy. Since nature endows all places with specific features, one obvious explanation to the concentration of population and firms in some regions is that they must have some natural advantage. On the contrary, sparseness and depopulation is very often related to absolute endowment disadvantages -lack of natural resources, bad climate, poor land quality, cold temperatures and propensity to disease- and/or long distances from the core economic centers, which penalizes either the relative prices of different goods or the relative profitability of different activities. Although Venables (1999) states that the degree of geographic determinism should not be exaggerated, it is clear that the impact of physical geography on development appears to derive from key relationships between climate and disease, climate and agricultural productivity, and also between location and technology transfer.

The main question is how much geography still matters for economic development. Gallup et al. (1999) find that location and climate have sizable effects on population density, as well as on income levels and growth rates -or even economic policy choice- through their effects on transport cost, disease burdens and agricultural productivity, among other channels. In particular, these authors regress the population density on geography variables such as distances to the coast and waterways, several measures of elevation, soil quality, availability of water and climate. In the international sample used, those factors explain 73% of the observed variability of the population density[2]. Nevertheless as stated in Roos (2005), this estimation might grossly exaggerate the importance of first nature due to the large number of independent variables used, what could lead to *multicollinearity*. Besides, he explains that there are other potential *missing variables* that are crucial in explaining the uneven distribution of population in the world. This is the case of institutional, historical, cultural and economic conditions, which are so diverse on the global level that threaten the consistency of the geography estimates.

On their side, Ellison and Glaeser (1997) and Kim (1999) think that a substantial portion of the observed geographic concentration of industries is affected by a wide range of natural advantages. In another paper, Ellison and Glaeser (1999) found that -apart from interfirm spillovers- geography is an important determinant of agglomeration, accounting for 50–86% of the observed variability. However, it can also been criticized that these figures are likely to overstate the importance of geography because of the broad definition of first nature. In fact they measure first nature with labor and capital endowments, such as labor costs, labor qualification and the size of the consumer market. Nevertheless, neither the regional endowments with mobile factors nor the prices of these factors are really exogenous. On the contrary, there might be a reverse causation -*simultaneity*- running from the presence of a particular industry in a region to the region's endowment with labor or capital. Actually if it is true that human and economic agglomerations can be explained by an accidental accumulation of favorable natural features, it is also true that households and firms interact on product and labor markets. If these markets are spatially segmented we expect economic activity taking place where people live, but at the same time we also expect people living where economic activity takes place.

[2] See other similar applications for Peru (Escobal and Torero 2005) and China (Ravallion 2007).

Consequently, it seems difficult to isolate the net influence of first nature on agglomeration since it is tightly joint to other factors belonging to what is called 'second nature'.

12.2.2 Second nature

Second nature factors are man-made 'agglomeration economies', i.e. interaction between economic agents among themselves (rather than the interaction between agents and nature), as well as knowledge and information spillovers, economies of intra-industry specialization, labor market economies or economies of scale in industry-specific public services, product differentiation and market size effects. Second nature, which is *endogeneous* to the economy, emphasizes the efficiency gains from proximity since interactions between economic agents (firms and consumers) are more efficient in densely packed areas than when people are widely dispersed (Kanbur and Venables 2007). These agglomeration forces can therefore create virtuous circles of self-reinforcing development in some regions while others lag behind. In this same direction, Fujita et al. (1999) demonstrate that the increasing returns to scale of some productive activities could be one of the keys to explain spatial economic inequality.

Venables (1999) show that second nature represents investment in transport and communication infrastructure, as well as its maintenance linking coastal to hinterland regions. In effect, although there is an association -in some places- among coastal locations, urbanization and growth, it is also true that investment in transportation and communication infrastructure linking coastal and interior areas facilitates hinterland development. It is known that access to hinterland resources is a geographic challenge to be overcome by infrastructure investment. Therefore, again we find a close connection between first and second nature. On the one hand, first nature geography constitutes an initial advantage that becomes usually amplified by second nature agglomeration forces. On the other hand, it is also known that the adverse effects of geography on economic growth can be overcome by different factors (Henderson 1999). As Krugman (1993) argues, first nature advantages generally tend to create second nature advantages through cumulative processes. These are decisive to explain the concentration of population that has taken place both during and after the industrialization process.

Even more, the new economic geography follows the new trade theory by showing how second nature effects can lead to a highly differentiated spatial organization of economic activity, even when the underlying physical geography is undifferentiated (Gallup et al. 1999). Krugman`s theory shows that agglomerations can be explained by *second nature alone* (net second nature). Similarly, Fujita et al. (1999) demonstrate that the increasing returns to scale of some productive activities could be the only key to explain spatial economic inequality.

It seems clear that first and second nature have an obvious incidence on agglomeration. Nevertheless it is necessary to compute the contribution of each net component as well as the first-second nature mixed effect. As stated before, this is the main aim of this paper.

12.2.3 The Spanish case

Referring to the particular case of Spain, Dobado (2006) coincides with Venables and Roos when considering first and second nature as non-contradictory but complementary, since real-world agglomerations are caused by both forces. In his opinion, the authentic peculiarity of Spanish regions -when compared to others in Southern Europe- consists in the existence of a large group of provinces with very low levels of population and GDP concentration close to another minor group with high densities. This is the so called duality core-periphery that, in the Spanish case is clearly conditioned by significant geographical -first nature- differences. The 'core' is constituted by Madrid and the coastal provinces, which in general terms, exhibit low altitude, humid climate and few extension, and concentrate the highest levels of GDP per area. The 'periphery' is located in a depopulated hinterland, with extreme temperatures and an abrupt topography.

Tirado et al. (2003) and Rosés (2003) analyze the role played by scale economies -second nature- on industrial agglomeration in Spain. They think that the major industrial concentration around Barcelona at the end of the Nineteenth Century was the result of both some initial natural advantages and a cumulative causation process linked to the increasing role of scale economies in production. They coincide with Krugman and Livas (1996) in considering that the protectionist policy -in the first decades of the Twentieth Century- weakened Barcelona's role in favor of capital cities located in geographical centers (Madrid and Saragossa). Transport costs from these core cities to domestic consumers could be minimized reinforcing the agglomeration tendencies and avoiding dispersion.

Viladecans (2004) also explains the uneven location of manufacturing activities in Spain as a result of two types of agglomeration economies, i.e. urbanization and localization economies. She states that the effect of specialization in one sector on a geographical area -localization economies- is a determining factor in the location of firms belonging to that sector. More precisely, the geographical distribution of most of the industrial sectors is influenced, to some extent, by the productive environment.

Ayuda et al. (2005) analyze the combined influence of first and second nature forces in population concentration as a two-step process. In effect, while geography can be expected to play a very important role in the Spanish pre-industrial economy, increasing returns seem to be the driving force of population concentration in the industrializing period. These authors explain that only those regions with particularly favorable resources for the location of certain types of industry could generate their own growth dynamics based on such comparative advantages. They compute the importance of natural or situational advantages on population density in the Spanish provinces at five different moments since 1787 to 2000. It covers the pre-industrial situation, the Spanish industrialization, the development process and the moments referred to a mature modern economy. The main results underscore the importance of geographical factors in explaining the distribution of the Spanish population in the last two centuries. Historically, the highest population densities have been found in the maritime or non-mountainous provinces, as well as in those areas with the highest annual rainfall.

Considering all this, it is clear that geographic considerations should be taken into account in empirical -and theoretical- studies of cross-country (or region) economic concentration. It is also evident that the term 'geography' should be split into first and second nature, since it includes not only natural advantages but also the scale economies or efficiency gains derived from proximity. Moreover, there is a combined or mixed effect of first-second nature on agglomeration that should be isolated to quantify to what extent natural endowments and man-made agglomeration economies mutually interacts. We can also conclude that from the concrete econometric modeling point of view, we must explicitly consider some potential problems, such as multicollinearity, relevant missing variables, endogeneity and spatial effects, if we want to reach reliable conclusions.

12.3 Data and model

12.3.1 Data

It is out aim to explain agglomeration from first and second nature elements. Hence we must define first what we understand for agglomeration and geography to find the appropriate indicators. Differently to Rosenthal and Strange (2001), we do not want to determine the degree of agglomeration but how geography -in general terms- influences the spatial distribution of activity. Regarding the endogenous variable, several measures have been used in the literature. This is the case of population, which has been applied to evaluate consumption, mainly when relying on the hypothesis that "firms follow people" (e.g. Graves 1979; Cragg and Kahn 1997; Knapp et al. 2001, for the US). Others, such as employment or GDP, are production indicators that would depend on the hypothesis that "people follow jobs" (e.g. Freeman 2001, in the US; Roos 2005, in Germany). Ciccone and Hall (1996) and Rapaport and Sachs (2003) decide on using population and employment densities as measures of agglomeration because they think that economic activity takes place where people live, and vice versa. Dobado (2004) proposes several indicators in absolute terms (area, GDP, population) or relative to the area (GDP or population density).

In order to make better comparisons with Roos' computations for German regions, we opt to use the relative GDP density –GDP per km^2- as the endogenous variable. He argues that this variable is more appropriate than population or employment densities to determine how geography influences the distribution of economic activity across a territory. In this way Delgado and Sánchez (1998) use the same variable to compute the evolution of income density in Spain. Since area is constant in each region every time, the evolution of this variable only depends on the quantity of the generated GDP.

Formally, the endogenous variable is defined as follows:

$$\log\left(gd_i\right) = \log\frac{Y_i/A_i}{\sum_i Y_i/A_i} = \frac{\log\left[Y_i/\sum_i Y_i\right]}{\log\left[A_i/\sum_i A_i\right]} \tag{12.1}$$

where Y is GDP and A_i is the area of region i. The relative GDP density of a region is its GDP density relative to the average density of all regions or, equivalently, the ratio of its share of GDP relative to the share of the country's total area. If $\log\left(gd_i\right)$ is equal to zero, region i's GDP share is equal to its area share. If it is larger (smaller) than zero, the region has a concentration of economic activity above (below) the average.

Next we define some good indicators to measure first and second nature effects. About first nature, we are interested in those geographical characteristics that are related to the distribution of economic activity. In general, this is the case of natural endowment, physical geography, relative location and political geography. Examples of natural endowment positively related to GDP density are agriculture, minerals, natural resources, good soil and water supply (Gallup et al. 1999; Rapaport and Sachs 2003). Some of these authors, as well as Gallup and Sachs (1998), Rappaport (2000) and Roos (2005), also include certain kind of physical geography indicators, such as altitude, latitude, distance to the coast and waterways, lying to the seashore (or being landlocked), navigable rivers and climate. Location is another geographical feature affecting agglomeration, which has been represented as relative distance to core -or other- regions or simply by the latitude-longitude Earth coordinates.

Following Ayuda et al. (2005) and Dobado (2004), we have chosen the annuall rainfall (*rainfall*) as a good proxy for agricultural potential, due to such dry conditions that are predominant in the Mediterranean regions (see in Table 12.1 a full description of the variables). We have also considered some climate variables, such as temperature (*temmin*, *temaver*, *temmax*, *tembel0*, *overcast*) and altitude (*altit*), as well as maritime length (*maritlim*, *coast*). We expect negative values for extreme temperatures and high altitudes, but a positive relationship between seashore extension and GDP density. Besides, we have included longitude and latitude, which are the X-Y Earth coordinates (*xcoo*, *ycoo*). As we will prove further, in Spain at present, being an Eastern Mediterranean region constitutes a relative advantage than lying to the Cantabric or the Atlantic seashores. However the North-South direction seems to be no longer significant in terms of agglomeration.

Table 12.1 Variable list for the Spanish provinces

Variable	Description	Units	Font	Period
gd	GDP per Area	Euros/sq. m.	FBBVA, FUNCAS	1930-2005
capit	Capital city	0-1	Self elaboration	-
altit	Altitude or elevation	meters	INE	-
temmin	Minimum temperature	Celsius	INE	1997-2005*
temaver	Average temperature	Celsius	INE	1997-2005*
temmax	Maximum temperature	Celsius	INE	1997-2005*
tembel0	Equal or below zero Celsius temperature	# days	INE	1997-2005*
rainfall	Total annual precipitation	millimeter	INE	1997-2005*
overcast	Overcast	# days	INE	1997-2005*
maritlim	Maritime limit	0-1	Self elaboration	-
coast	Seashore length	kilometers	INE	-
xcoo	Longitude (X-coordinate)	grades	Self elaboration	-
ycoo	Latitude (Y-coordinate)	grades	Self elaboration	-
Pop	Population	people	FBBVA, FUNCAS	1930-2005
Prod	GDP per employee	Euros	FBBVA, FUNCAS	1930-2005

* Average of the period, *INE* Spanish National Institute for Statistics, *FBBVA* Foundation of the *Bilbao Vizcaya Argentaria* Bank.

Political geography has also been highlighted by Mathias (1980), McCallum (1995) and Roos (2005) who consider that agglomeration is positive or negatively affected by containing a capital city or being a border region, respectively. In this case, we have considered a dummy variable to indicate the presence of a capital city in a region (*capit*). Similarly to the German regions (Roos 2005), the Spanish autonomies concentrate a lot of legislative and executive power in their capital cities. This is why provinces with a capital city have better access to information about regional government investment and decision plans (Ades and Glaeser 1995; Funck 1995; Ayuda et al. 2005).

In order to measure man-made agglomeration economies (second nature) we have also followed Roos (2005) what allows us to make better comparisons with this case. He chose total population (*pop*) and labor productivity (*prod*) since on aggregate levels both variables can capture many agglomeration economies, i.e. informational spillovers and labor market economies. Population could be considered as an indirect measure of agglomeration economies. In effect, as stated in Henderson (1988) if agglomeration economies exist in an area, labor productivity should rise in the level of population (employment). Other indicators, such as population density (proposed in Gallup et al. 1999), provide not so clear relationship with GDP density (e.g. some densely/sparsely populated areas are rich whereas others are poor, which are the cases of Western Europe/New Zealand and Indonesia/African Sahel, respectively).

12.3.2 Model

Three forces operate in forming agglomerations: an unobservable direct effect of first nature, a first nature effect working through induced agglomeration economies and a direct effect of second nature, which would exist even without any first nature forces. In order to get a better knowledge of these effects, Roos (2005) states a methodology based on analysis of variance (ANOVA). The total variance V of the dependent variable can be decomposed into four parts:

$$V = V_u + V_f + V_s + V_{fs} \tag{12.2}$$

where V is the total variance of the dependence variable, V_u is the unexplained variance, V_f is the variance explained by first nature alone, V_s is the variance explained by second nature alone and V_{fs} is the variance explained by a combination of both forces.

ANOVA is employed to infer the unobservable importance of first nature alone indirectly, as well as to assess about the relative importance of first and second nature forces. It is a four-step process that proceeds as follows:

1. Since man-made agglomeration effects (second nature) are usually triggered by natural advantages (first nature), we must first identify the net from the gross second nature effect. For this purpose, we regress two gross second nature variables on first nature. These regressions explain how much of the gross second nature effects are caused by purely first nature. By mean of the residuals of the regressions, we filter the net from the gross second nature variables.
2. We estimate how much of GDP per area variance can be explained by gross ($V_s + V_{fs}$) and net (V_s) second nature advantages. These calculations can be derived from the results of two regressions of GDP density on both gross and net second nature variables.
3. We estimate how much of GDP per area variance can be explained jointly by first and second nature ($V_f + V_s + V_{fs}$). The total effect of first and second nature can be obtained from a regression, using first and net second nature variables as explanatory variables.
4. We calculate the difference between the result in step 3 (total effect of first and second nature) and step 2 (total effect of second nature), which is the importance of first nature alone (V_f) on GDP per area.

Next, we will explain the whole process in depth.

Since first and second nature are interrelated, in a *first step* it is necessary to disentangle the second nature variables (population and GDP per worker) empirically. For that purpose, we can regress them on geography and take the residuals $\hat{\pi}$ and $\hat{\rho}$ as variables of net second nature forces:

$$\log\left(pop_i\right) = \gamma_0 + \sum_{k=1}^{K} \gamma_k f_{ki} + \pi_i \qquad (12.3)$$

$$\log\left(prod_i\right) = \rho_0 + \sum_{1}^{K} \rho_k f_{ki} + \delta_i$$

where pop_i and $prod_i$ are total population and GDP per worker in region i, f_{ki} is the group of k geography variables, γ, ρ are coefficients and π, δ are the error terms of the regressions.

While variables $s_{mi} = \{\log(pop_i, \log(prod_i)\}$ are 'gross' second nature variables, the residuals of these regressions $\hat{s}_{mi} = \left\{\hat{\pi}_i, \hat{\rho}_i\right\}$ could be taken as geography-filtered or net second nature forces. The introduction of these sets of variables, s_{mi}, $\hat{s}_{mi}$, as explanatory variables will allow to evaluate the total influence of gross and net second nature variables on GDP density.

In a *second step* we can compute the effects of total -both gross and net- second nature variables on GDP per area. In this fashion, the gross second nature variables influence is obtained with the estimation of the following equation:

$$\log\left(gd_i\right) = \alpha_0 + \sum_{m=1}^{M} \phi_m s_{mi} + \varepsilon_i \tag{12.4}$$

The resulting determination coefficient indicates this gross effect of second nature:

$$R_{gs}^2 = \frac{\left(V_s + V_{fs}\right)}{V} \tag{12.5}$$

Regarding the net effect of second nature on GDP per area, it is derived from the estimation of the following equation:

$$\log\left(gd_i\right) = \alpha_0 + \sum_{m=1}^{M} \phi_m \hat{s}_{mi} + \varepsilon_i \tag{12.6}$$

The net effect of second nature on agglomeration can be expressed as:

$$R_{ns}^2 = \frac{V_s}{V} \tag{12.7}$$

Therefore, the mixed effect of the interaction between first and second nature on GDP density can be extracted as follows:

$$\frac{V_{fs}}{V} = R_{gs}^2 - R_{ns}^2 \tag{12.8}$$

In the *third step*, we measure the total effect of first and second nature on GDP per area. We could simply include, in another equation, the gross second nature variables as regressors together with a set of first nature indicators. However, this could bias the estimates of the first nature coefficients since first nature also has an effect on the second nature variables. In order to adjust the later for the former, we specify a regression of GDP per area on first and *net* second nature variables, which avoids the stochastic regressors problem:

$$\log\left(gd_i\right) = \alpha_0 + \sum_{k=1}^{K} \phi_k f_{ki} + \sum_{m=1}^{M} \phi_m \hat{s}_{mi} + \varepsilon_i \tag{12.9}$$

The joint importance of first and second nature is measured by the corresponding determination coefficient:

$$R^2_{f+s} = \frac{V_f + V_{fs} + V_s}{V} \tag{12.10}$$

In the *forth step*, we derive the net importance of first nature on GDP density from the results of the previous estimations:

$$\frac{V_f}{V} = R^2_{f+s} - R^2_{gs} \tag{12.11}$$

The estimation of Eqs. 12.4, 12.6 and 12.9 by Ordinary Least Squares (OLS) could lead to biased results due to the presence of endogeneity on some of the explanatory variables and/or spatial effects on the residuals. Roos (2005) and Gallup et al. (1999) only consider the first problem but omit the second.

In effect, on the one hand endogeneity in a regressor can lead to a well-known simultaneity bias in the OLS estimates. Even in the pure-geography variables there could be different degrees of exogeneity. Physical geography variables (temperature, coast, etc.) can be considered as exogeneous since they do no depend on underlying economic forces. However political geography could have more endogeneous elements; e.g. the location of state capitals, though do not change very often, are possibly the result of the economic importance of the corresponding city. Moreover, the second nature variables (population and productivity) are much more endogenous and simultaneously determined with GDP density.

On the other hand, spatial autocorrelation and/or spatial heterogeneity in the OLS residuals are also causes of misspecification problems in the regression (see Anselin 1988 for a complete view of this topic). They must be tested and corrected, as will be shown hereafter.

12.4 Evolution of the spatial distribution of GDP per Area

In this section we explore the geographic dimension of GDP per area for the continental Spanish provinces (47 provinces in total). We have excluded the Balearic and Canary Islands and the African cities, Ceuta and Melilla, since these administrative regions are not comparable in size with the others (population and GDP densities are extremely high). In order to explore these issues, we need a data set consistently defined over the century. For that purpose, we have used the GDP, employment and population series proposed by Alcaide (2003), for 1930 to 2000, and Alcaide and Alcaide (2007), for 2000 to 2005. The data on area are extracted from the Spanish Office for Statistics (INE) databank[3].

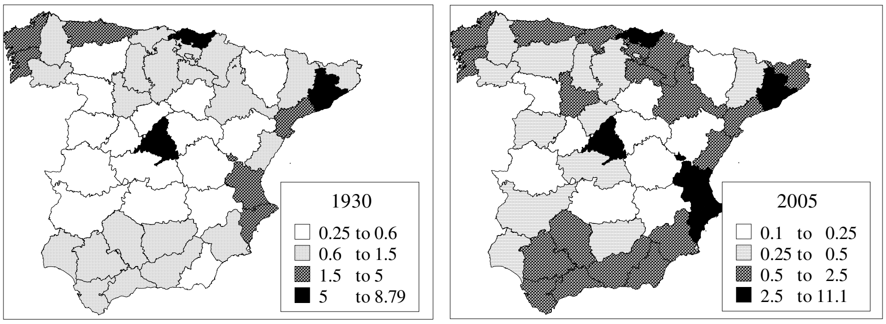

Fig. 12.1 Choropleth maps of relative GDP per Area (1=national GDP/km^2)[4]

Actually, we have selected 5 periods: 1930, 1950, 1970, 1990 and 2005, since they constitute good references for our analysis, corresponding to relevant facts related to Spanish economic history. In effect, in 1930 Spain put an end to General Primo de Rivera's dictatorship. The economy enjoyed a prosperous moment thanks to a large public expenditure. Road and rail networks improved driving force to the development of industry and employment. At that moment, there were some industrialized enclaves, especially in the Axis Madrid-North-Barcelona, as well as other provinces in the Cantabric and Mediterranean Coast (Fig. 12.1). However, during the mid 30's and 40's the economic crisis and the Civil War stopped this process leading to an autarkical regime and recession. In 1950, approximately in the middle of General Franco's dictatorship, Spain had experienced a ruralization process with an increasing participation of agricultural sector. Rationing of food, commodities and energetic resources expelled the Spanish population from cities to rural places.

During the 50's and 60's, the incipient political and economic openness set the basis for a decisive industrialization and tertiarization process. The Development Plans produced economic prosperity and liberalization, leading to new economic poles in Galicia, Castile, Andalusia, Aragón and Extremadura. This processes joint to a new great exodus from rural zones to industrial and urbanized areas –inland and abroad- helped to equilibrate

[3] This data are available in the INE webpage: http://www.ine.es

[4] The variables have been classified with a method called "natural breaks", which allow identifying breakpoints between classes using Jenks optimization (Jenks and Caspall 1971). This method is rather complex, but basically it minimizes the sum of the variance within each of the classes, finding groupings and patterns inherent in the data.

the traditional inequality in the distribution of wealth across the Spanish territory. In 1970, close to the ending of Franco's regime, Spain was no more rural but urban.

By the beginning of the 1990's, Spain is one of the democracies belonging to the Economic European Community. In the late 80's, a strict plan of economic stabilization, based on a traumatic industrial restructuring and liberalization customs, reformed the Spanish economy. The transfer of funds proceeding from the EEC made possible an ambitious policy of public investments in infrastructures. Nevertheless, income disparities across the Spanish regions still remained and even deepened. In 2005, economic development depicted a peculiar structure similar to a star, with its centre in Madrid and the axis in the peripheral areas: the vast Mediterranean metropolitan areas, coastal Andalusia and Seville, coastal Galicia and the Cantabric regions. In addition, inside this big star, there was a vast rural desert, only broken by a few urban oases, like Valladolid, Saragossa, Badajoz, Burgos, Álava and Navarre.

Table 12.2 Descriptive Statistics of Relative GDP per Area

Variable	Mean	Pearson CV	Minimum	Q1	Median	Q3	Maximum
GDP 1930	1.38	1.30	0.26	0.48	0.74	1.37	8.78
GDP 1950	1.42	1.42	0.20	0.48	0.72	1.39	9.03
GDP 1970	1.50	1.66	0.14	0.32	0.54	1.41	10.62
GDP 1990	1.45	1.64	0.10	0.27	0.51	1.40	10.89
GDP 2005	1.44	1.61	0.10	0.26	0.57	1.41	11.01

GDP relative GDP per area (1=national GDP per km^2), *CV* coefficient of variation, *Q1*, *Q3* first and third quartiles, 1=national GDP/km^2

Fig. 12.2 plots the density functions for Spain-log relative GPD per km^2. These density plots 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, 0 on the horizontal axis indicates Spanish average GDP, 2 indicates twice this average, and so on.

This Fig. shows the evolution of the dependent variable over time from 1930 until 2005. It is an interesting graph in which the distributions are more or less bimodal with a second mode around two standard deviational units above the mean. The distributions in 1930 and 1950 are quite similar and non-normally distributed (the Jarque-Bera normality test rejects log-normality with 95% of confidence, as shown in Table 12.3). Both exhibit a main skewed mode just on the mean and a slight minor mode two standard deviational units above the mean. Nevertheless, the central mass of the distribution significantly decreased in 1970 to reach the lowest point in the 2005. Log-normality could be accepted, though only at 0.28 level. In the last decades, the main mode moves around one standard deviational unit below the mean whereas the second mode allocates throughout the second half of the distribution, particularly around two standard deviational units above the mean.

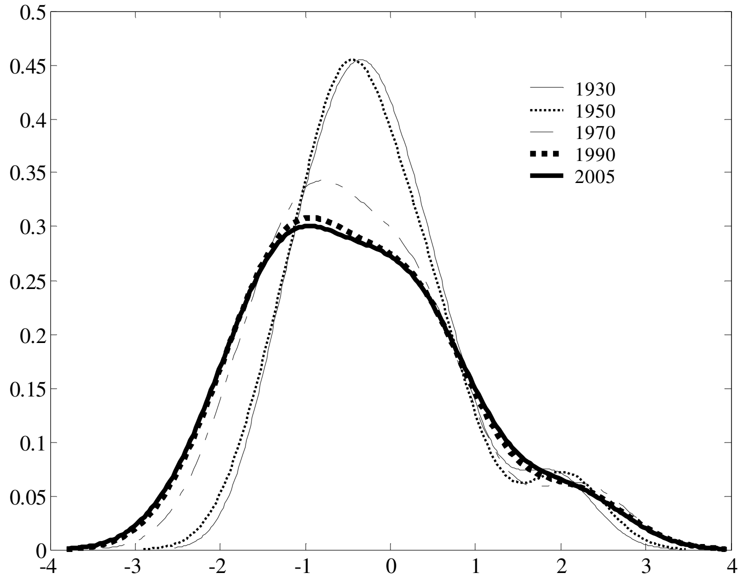

Fig. 12.2 Kernel density estimates of log relative GDP per area

That is to say, compared with 1930 and 1950, more regions reported in 1970, 1990 and 2005, GDP either 50 percent of the Spanish average or almost twice the Spanish average. Moreover these modes situated below and above the Spanish average may reflect the existence of two groups of provinces with GDP density converging toward a lower and higher GDP density levels than the rest of provinces, respectively. The progressive deconcentration of probability mass from 100% can be interpreted as evidence for slight divergence. As stated before, in 1930 and 1950 Spain was mainly an underdeveloped rural country, only depicted by few economic poles located in the traditional thriving regions. GDP was more or less uniformly distributed across the country with these exceptions, which constitute a second mode around two standard deviations above the mean. During the following decades, the strong economic development and profound social changes deepened this picture leading to a spillover process that principally benefited other contiguous regions. Economic prosperity caught up the whole country but not with the same intensity. As shown in Fig. 12.2, different modes in 2005 suggest dissimilar growth velocities inside a country which is more or less divided into two subspaces. On the one hand, coastal (and Madrid) thriving regions constitute a more homogeneous area in terms of economic development, though traditional enclaves (the Bask Country, Catalonia, Navarre and Madrid) still remain the leaders (second mode). On the other hand, the hinterland lagging regions are becoming a vast rural wasteland with the exception of some provinces (mainly the region capitals), which absorbs most of the GDP generated in this subspace (first mode).

This result is similar to others in the literature of Spanish regions and urban areas (see, for example, Goerlich et al. 2002; Garrido 2002; Domínguez 2003; Pulido and López 2003; Dobado 2006; Mella and Chasco 2006). Nevertheless, it contrasts somehow with the results shown in Roos for the German regions in 2000, which show a skewed non-normal distribution with a prominent second mode about 1.5 deviational units above the mean.

As well, during the whole period we can also find some kind of general spatial trend in GDP per area, as shown in Fig. 12.1: from the inland (low GDP density) to the coastal provinces (high GDPensity), with the exception of Madrid. This is a spatial effect called 'spatial autocorrelation', which can be defined as the coincidence of value similarity with locational similarity (Anselin 2000). There is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values. The measurement of global spatial autocorrelation is based on the Moran's I statistic, which is the most widely-known measure of spatial clustering (Cliff and Ord 1973, 1981). This statistic is written as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{12.12}$$

where y_i is the relative log of GDP per area in province i; $\overline{y}$ is the average value of variable 'y'; w_{ij} is an element of a spatial weights matrix, $\mathbf{W}$, such that each element is set equal to 1 if province j has a common border with

i, and 0 otherwise; and S_0 is a scaling factor equal to the sum of all elements of W. Similar results have been obtained with other specifications[5].

Table 12.3 Normality and spatial autocorrelation tests of log relative GDP/Area

Variable	1930	1950	1970	1990	2005
Jarque Bera normality test	5.95**	7.42**	5.08*	3.00	2.56
Moran's I spatial autocorrelation test	0.20**	0.17**	0.19**	0.18**	0.18**

** significant at 5%, * significant at 10%. Inference for Moran's I test is based on the permutation approach (999 permutations)

In the given period, the GDP per area distributions display a significant degree of spatial autocorrelation (Table 12.3): the magnitude of the Moran's I tests are high and significant at $p < 0.05$, which is above its expected value under the null hypothesis of no spatial autocorrelation, E[I] = –0.02 (approximately in all the cases). Inference is based on the permutation approach (999 permutations), since not all the series distributes normally (Anselin 1995). Though we should be cautious because it is a large sample test, this result suggests that the evolution of production distribution appears to be somewhat clustered in nature. That is, provinces with very relatively high/low production density levels tend to be located near other provinces with high/low production density levels more often than would be expected as a result of purely random factors. If this is the case, then each province should not be viewed as an independent observation.

Fig. 12.3 provides a more disaggregated view of the nature of spatial autocorrelation for production density by means of a Moran scatterplot (Anselin 1996), which plots the standardized log-relative production density of a province (LG) against its spatial lag (also standardized), W_LG. A province's spatial lag is a weighted average of the productions of its neighboring provinces, with the weights being obtained from a row-standardized spatial weight matrix (**W**). The four different quadrants of the scatterplot identify four types of local spatial association between a prov-

[5] The role of the spatial weight matrix is to introduce the notion of a neighborhood set for each province. As it is common in spatial econometrics applications, we have row-standardized this matrix dividing each element in a row by the corresponding row sum (see Anselin 1988). We have used other specifications for the spatial weight matrix. These include an inverse distance matrix (such that each element w_{ij} is set equal to the inverse of the squared distance between provinces i and j), and a matrix obtained from a 200 km distance threshold to define a province's neighborhood set (as stated in Rey and Montouri 1999).

ince and its neighbors: HH (‘High-High’), LL (‘Low-Low’), LH (‘Low-High’) and HL (‘High-Low’).

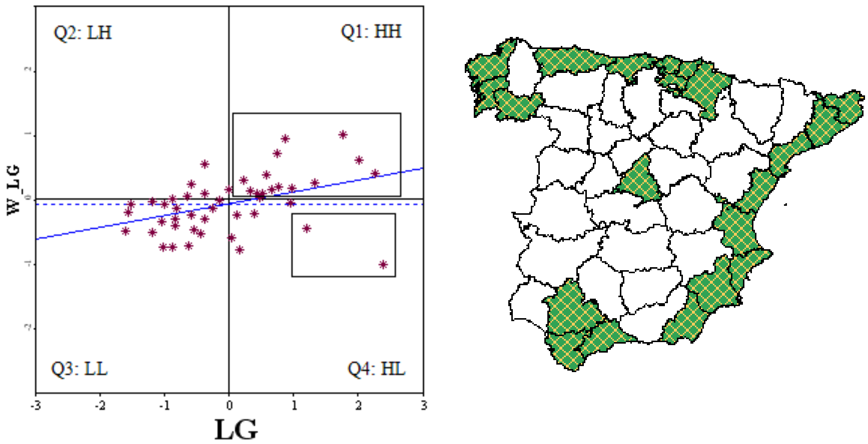

Fig. 12.3 Moran scatterplot of log relative GDP per Area in 2005 (left). Map with the selection of provinces ever located in Quadrant 1, plus Madrid and Valencia

In Quadrant 1, the Moran scatterplot represents those high-GDP density provinces that are surrounded by high-GDP density neighbors, which have been highlighted in the map. It can be appreciated that they are all mainly located in the Coastal limits of the country. We have also selected Madrid and Valencia, located in Quadrant 4, in which we can find the group of high production density provinces surrounded by low production density neighbors. Quadrants 2 and 4 represent negative spatial dependence, while Quadrants 1 and 3 belong to positive forms of spatial dependence.

In the map we have selected all the provinces ever located in Quadrant 1 (high-high association) during the considered periods (1930, 1950, 1970, 1990, and 2005). We have also included Madrid and Valencia due to the major level of agglomeration effects detected around these regions (OECD 2000, Peeters and Chasco 2006). Therefore, the Moran scatterplot reveal the presence of spatial heterogeneity in the form of two clusters of production density in Spain: the coastal provinces, with the spatial discontinuity of Madrid (higher production density) and the hinterland (lower production density).

These results agree with the bimodal distributions shown in Fig. 12.2, which reflect a situation of two groups of provinces with GDP density levels converging toward a lower and higher GDP density levels than the rest of provinces, respectively. That is to say, spatial autocorrelation and spatial heterogeneity are two effects that must be tested when modeling GDP density since they could lead to biased coefficients if they are not adequately taken into account.

12.5 Influence of geography on the location of production

In this chapter, we apply the ANOVA methodology proposed in Roos (2005) for German regions in 2000. In our case, we present a dynamic analysis for the last century testing not only for endogeneity but also spatial effects in the residuals. As stated before, it is a four-step analysis that proceeds as follows: 1) we filter gross second nature indicators from first nature interrelations; 2) we estimate how much of GDP per area variance can be explained by gross (V_s+V_{fs}) and net (V_s) second nature advantages; 3) we estimate how much of GDP per area variance can be explained jointly by gross first and second nature (V_f+V_s+V_{fs})); and 4) we calculate the difference between the result in step three and two, which is the importance of first nature alone (V_f).

12.5.1 Filtering gross second nature from first nature elements

In order to disentangle empirically the second nature variables (population and GDP per worker) from first nature interactions, we proceed to regress them on geography and take the residuals as variables of net second nature forces (see Eq. 12.3). Table 12.4 presents the results of the final regressions of the second nature variables on first nature, after elimination of insignificant variables[6]. The fit of both population and labor productivity equations are good, even higher than those found in Roos' application for Germany. Measured by R^2, we can say that, in average during the Twentieth, first nature itself explains about 55% of the second nature's spatial variation.

The capital dummy has the largest influence on both second nature variables. Particularly in the population equations, it has an increasing im-

[6] We follow a general-to-specific modeling strategy. In a first regression, we include the complete set of first nature variables. In a step-by-step sequenced process, we exclude the variable with the lowest t-statistic and estimate the remaining equation again. This procedure is repeated until all coefficients are significantly different from zero at the 10% level.

pact[7] that ranges from 51% in 1930, to 116% in 2005. We should also highlight the recent influence of the coast dummy.

Alternatively, in 2005 changes from zero to one (non-coastal to coastal) cause a population increase of 65% but a labor productivity decrease of 8%. This apparently contradictory result -population increase joint to productivity reduction in coastal regions- could be explained by the existence in most Mediterranean provinces of a predominant less-productive 'sun and beach' tourism activity and certain hand-worker intensive industries.

We have filtered the residuals of these 10 regressions, *pi*, *del*, which will be considered as net second nature forces.

Table 12.4 Second nature on first nature OLS regression results

Depend. variable	Log(pop)					Log(prod)				
	1930	1950	1970	1990	2005	1930	1950	1970	1990	2005
constant	13.3***	13.4***	13.4***	13.4***	13.6***	2.77***	3.98***	8.65***	8.23***	9.55***
capit	0.41**	0.47**	0.63***	0.77***	0.77**	0.15**	0.12*	0.15***	0.08*	
altit								-0.0005**		-0.0002**
temmin	0.04*	0.04*	0.08***	0.07**	0.08***			0.06***	0.05**	
temaver						-0.10***	-0.07***	-0.11***	-0.08**	-0.04***
temmax									0.03*	
rainfall	0.001**	0.001**	0.001**	0.001*						
tembel0						-0.008***	-0.007***			-0.003***
overcast	-0.01***	-0.01***	-0.01**	-0.10**	-0.01**					
maritlim						-0.0003*		-0.0004**		
coast				0.33*	0.50**					-0.08**
xcoo						5.2e-7***	4.9e-7***	6.9e-7***	6.0e-7***	3.5e-7***
ycoo								-3.6e-7*		
R2	0.48	0.49	0.56	0.64	0.65	0.51	0.39	0.60	0.50	0.60
Net 2nd	pi_{30}	pi_{50}	pi_{70}	pi_{90}	pi_{05}	del_{30}	del_{50}	del_{70}	del_{90}	del_{05}

*** significant at 0.01, ** significant at 0.05, * significant at 0.1, *Log(pop)* log population, *Log(prod)* log labor productivity, *pi, del* residuals of Eq. 12.3.

7 In semi-logarithmic equations, the dependent variable changes by [exp(*b*)-1]·100 percent if the explanatory variable changes from zero to one unit, where *b* is the explanatory variable coefficient.

12.5.2 Second nature effects on GDP per Area

In this step, we compute second nature effects on GDP per area with the estimation of two equations. Firstly, we regress the log-relative GDP per area on population and labor productivity. The resulting determination coefficient will indicate the second nature gross effect $R_{gs}^2 = \left(V_s + V_{fs}\right)/V$. Secondly, the second nature net effect on GDP per area is obtained from the estimation of this variable on the residuals, *pi*, *del*, derived from the last estimations, with the help of the corresponding determination coefficient $R_{ns}^2 = V_s/V$.

As stated in Roos (2005), one problem is that the second nature variables are endogenous and simultaneously determined with GDP. This might lead to the well-known simultaneity bias in the regressions violating the necessary conditions to obtain estimates with good properties. The instrumental variables estimation is the standard approach to overcome the consequences of simultaneity, i.e. biasness, inefficiency and inconsistency on OLS-estimators.

The principle of the IV estimation is based on the existence of a set of instruments that are strongly correlated to the original endogenous variables but asymptotically uncorrelated to the error term. Once these instruments are identified, they are used to construct a proxy for the explanatory endogenous variables which consists of their predicted values in a regression on both the instruments and the exogenous variables. However, it is very difficult to find such instruments because most socioeconomic variables will be endogenous as well. In the standard simultaneous equations framework, the instruments are the ‘excluded’ exogenous variables.

In our case, in order to decide whether we need IV estimation, we have first analyzed the potential system feedbacks between the dependent variable, log-relative GDP per Area, and the four second nature explanatory variables, i.e. population, labor productivity and the OLS residuals (*pi*, *del*) found in Table 12.4 estimations. For this purpose, we have used the *Durbin-Wu-Haussman* (DWH) test, which is an ‘exogeneity test’ (Anselin 1999) that compares the IV and OLS estimates assuming the former are consistent. Although consistent, in small samples the IV estimates may be inferior to OLS in terms of mean squared error. This test reports the confidence level at which consistency of OLS estimates can be rejected. In fact, it is an F test with (k^*, $n–k–k^*$) degrees of freedom on the null hypothesis of exogeneity of a k^* subset of the total k explanatory variables, with n as the number of observations (for technical issues, see Davidson and

McKinnon 1993)[8]. Since we need to estimate IV equations to perform this test, we must first decide the set of adequate instruments for each potential stochastic regressor. As stated above, they should be correlated to the original endogenous variables but asymptotically uncorrelated to the error term.

Table 12.5 Instruments and endogeneity tests in second nature effect regressions

Gross second		Instruments	DWH	Net second		Instruments	DWH
Log (pop)	1930	pi30, tembel0	3.5*	pi	1930	pi50	0.0
	1950	lpo30	0.2		1950	pi30	0.1
	1970	lpo50	61***		1970	pi50	13***
	1990	lpo70	5.0**		1990	pi70	0.0
	2005	lpo90	0.7		2005	pi90	0.8
Log (prod)	1930	del30, lpr70	0.8	del	1930	del50, lpr30	12***
	1950	lpr30, del50	3.2*		1950	del30, lpr50	16***
	1970	lpr50, del70	2.1		1970	del50, lpr70, lpr50	3.3**
	1990	lpr70	9.1***		1990	del70, lpr90	5.8**
	2005	lpr90, del05, xcoo	1.2		2005	del90, lpr05, lpr90	0.6

Log(pop) log population, *Log(prod)* log labor productivity, *pi* residual of the regression of log population on first nature variables, *del*: residual of the regression of log labor productivity on first nature variables, *tembel0* # days with temperatures below zero Celsius, *xcoo* X-coordinate, *DWH* Durbin-Wu-Haussman exogeneity test, *** significant at 0.01, ** significant at 0.05, * significant at 0.1.

Roos proposes to use mainly time-lagged variables as instruments, since they are highly correlated with the actual variables but also non-contemporary correlated with the errors[9]. Besides, we have also considered other space and/or time lagged second nature variables as well as ‘excluded’ first nature explanatory variables. In all cases, we have selected only those instruments more correlated with the corresponding endogenous regressor and less correlated with OLS error terms[10]. In Table 12.5, we

[8] As shown in Anselin (1999), DWH test is consistent with spatially autocorrelated OLS residuals.

[9] Non-contemporary dependence between regressors and the error terms lead to asymptotically unbiased estimators only in absence of temporal autocorrelation. However, in our case it is difficult to suppose time independence between the error terms what could somewhat affect our results.

[10] The goodness of the instruments can be proved with the help of the Sargan test, which contrasts the null hypothesis that a group of s instruments of q regressors are valid. This is a Chi-2 test with (s–q) degress of freedom that rejects the null when at least one of the instruments is correlated with the error term (Sargan

have shown the instruments definitely used in each equation, as well as the results of the *Durbin-Wu-Haussman* (DWH) test.

Table 12.6 Regression results of GDP per area on second nature variables

	Gross 2nd nature					Net 2nd nature				
Period	1930	1950	1970	1990	2005	1930	1950	1970	1990	2005
Estimation	IV	IV	IV	IV	OLS	IV	IV	IV	IV	OLS
Constant	-14.6**	-16.1**	-23.1**	-36.3**	-45.2**	-0.14	-0.16	-0.33*	-0.39*	-0.39**
Log(pop)	0.92**	0.72**	0.77**	0.91**	0.99**					
Log(prod)	1.97**	2.16**	2.41**	2.91**	3.56**					
pi						0.58	0.51	0.83**	0.89**	0.98**
del						2.85**	2.96**	3.11*	3.54*	2.88
R-squared	0.74	0.69	0.71	0.82	0.81	0.45	0.51	0.36	0.36	0.27
Sp. Chow	34.4**	40.2**	35.3**	27.4**	10.4**	75.9**	80.5**	106.1**	107.2**	105.9**
LM (sp.er.)	7.49**	14.4**	22.7**	20.7**	7.03**	5.19*	8.25*	7.67	7.58**	5.99*

Log(pop) log population, *Log(prod)* log labor productivity, *pi* residual of the regression of log population on first nature variables, *del* residual of the regression of log labor productivity on first nature variables, *Sp. Chow* spatial Chow test, *LM (sp.er.)* Lagrange Multiplier test for spatial error autocorrelation, ** significant at 0.01, * significant at 0.05.

Results show a high degree of simultaneity in some of the second nature regressors with respect to log-relative GDP per area. This is the case of log-population, for 1970 and 1990 equations, and log-labor productivity, for 1950 and 1990 equations. Regarding net second nature variables, population series (*pi*) are mainly exogenous, though productivity variables (*del*) exhibit clear endogeneity except for 2005. As a consequence, both Eqs. 12.4 and 12.6 must be estimated by IV for all the periods, with the exception of 2005, which is the only case of total absence of endogeneity in the regressors.

In Table 12.6, we show the estimation results of Eqs. 12.4 and 12.6, in which log-relative GDP per Area is regressed on gross and net second nature variables, respectively. Being aware of the potential drawback coming from the asymptotic considerations of all statistical inference for IV estimates (which may not be very reliable for small data sets), we have com-

1964). In our case, we can clearly accept the null with a confidence level of 0.99. All the computations can be obtained upon request from the authors.

puted the so-called asymptotic *t*-tests as a ratio of the estimate to its asymptotic standard error.

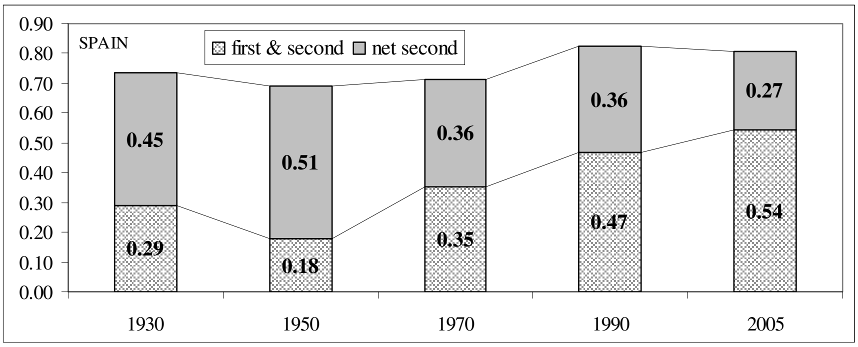

Fig. 12.4 Evolution of the impact of second nature forces on GDP density

As stated in Anselin (1988, pp. 244), in the IV estimation approach the residuals have a zero mean, so than the standard variance decomposition can be obtained and a determination coefficient can be computed in the usual manner (the ratio of the variance of the predicted values over the variance of the observed values for the dependent variable). Consequently, the five regressions on population and productivity provide a determination coefficient R^2_{gs} between 0.69 (year 1950) and 0.82 (year 1990), which is the share of GDP density variance that is explained by gross second nature effects. The estimation of the other five equations yield $0.27 \le R^2_{ns} \le 0.51$, which is the importance of net second nature on GDP density. Regarding the mixed effect of the interaction between first and second nature on GDP density (R^2_{fs}), it can be extracted as the difference between R^2_{gs} and R^2_{ns} (Eq. 12.8). Fig. 12.4 summarizes the results for the estimations of Table 12.6.

To some extent, second nature has increased its importance on GDP density in Spain during the last century, accounting for 0.74 in 1930 to 0.81 in 2005. Roos found that only 65% of German GDP density in 2000 was caused by gross second nature. He decomposed it into a mixed-indirect effect (29%) and a net-direct effect (36%). In Spain, net second nature forces reach the maximum effect in 1950 (0.51) and progressively decline to 0.27 in 2005. Pertaining to the interaction effect of physical geography and agglomeration economies, it registers a growing trend from 0.29 (1930) to 0.54 (2005), almost doubling -at this moment- Roos' results for Germany. This result shows the more and more importance of the interaction between economic agents and nature as determinants of GDP density. This is clear in certain economic activities related with tourism, which has been the main engine of Spanish economy since the 60's.

The final line of diagnostics in Table 12.6 reports an asymptotic LM test for spatial error autocorrelation[11] (Anselin 1999). In addition, we have also tested for spatial heterogeneity in the errors, in the form of two subspaces, as detected before for GDP density distributions (Fig. 12.3), i.e. higher/lower GDP density provinces (coast/hinterland, respectively). For this purpose, we use the spatial Chow test proposed by Anselin (1990), in which the null hypothesis states that the coefficients are the same in all regimes. It is based on an asymptotic Wald statistic, distributed as a χ^2 distribution with $[(m-1)\cdot k]$ degrees of freedom (m being the number of regimes). In Table 12.6, the null hypothesis on the joint equality of coefficients is clearly rejected by the Chow-Wald test in all the regressions, i.e. their values are sufficiently extreme for a distribution with three degrees of freedom. Therefore, both spatial effects are present in the regressions on second nature variables demonstrating the existence of non-randomness in the error terms. It is known that sometimes, spatial autocorrelation in the residuals may be induced by a strong spatial heterogeneity that is not correctly modeled by spatial dependence specifications (Brunsdon et al. 1999).

Consequently, in order to capture the polarization pattern previously observed in the distribution of GDP density among the Spanish provinces, we allow cross-region parameter variation in a *spatial regimes model* with two subspaces corresponding to coastal provinces (plus Madrid) and the rest of inland provinces. There are 21 provinces included in the higher GDP density group (coast) and 26 provinces included in the lower GDP density group (hinterland).

As shown in Table 12.7, spatial instability has important effects on the determination coefficients. In general terms, they are higher in the coastal subspace than in the hinterland, mainly for net second nature. In Fig. 12.5 we have graphed the dynamics experienced by both groups. Differences in GDP density inside the leading group are much due to net agglomeration economies, whereas differences in lower GDP density group depend more on mixed effects.

On its side, spatial autocorrelation in the residuals disappear in all the equations (the LM tests are not significant) with the exception of gross second nature in 1970 and 1990. As a result in most cases, the spatial regimes model controls for the presence of both spatial effects in second na-

[11] This test has been constructed in the same fashion as in Burridge (1980). The spatial weight matrix is specified as in equation 11.

ture equations. This result confirms our initial hypothesis about the importance of taking into account spatial instability in GDP density distributions.

Table 12.7 Regression results of GDP/area on second nature in 2 spatial regimes

		Gross second nature					Net second nature				
Period		1930	1950	1970	1990	2005	1930	1950	1970	1990	2005
Estimation		IV	IV	IV	IV	OLS	IV	IV	IV	IV	OLS
Const	Inland	-10**	-13**	-14**	-22**	-20*	-0.7**	-0.7**	-1.1**	-1.2**	-1.2**
	Coast	-11**	-11**	-19**	-31**	-40**	0.5**	0.5**	0.5**	0.5**	-0.5**
Log (pop)	Inland	0.60**	0.60**	0.50**	0.62**	0.69**					
	Coast	0.68**	0.45**	0.57**	0.63**	0.71**					
Log (prod)	Inland	1.40**	1.72**	1.17*	1.59*	1.16					
	Coast	1.66**	1.93**	2.21**	2.80**	3.47**					
pi	Inland						0.13	0.28	0.27	0.37	0.33
	Coast						0.86**	0.77**	0.84**	0.89**	0.95**
del	Inland						0.86	1.63*	0.95	1.42**	0.23
	Coast						1.81**	1.94**	2.71*	2.52*	2.07
R2	Inland	0.69	0.70	0.44	0.59	0.56	0.30	0.46	0.09	0.15	0.06
	Coast	0.77	0.71	0.73	0.86	0.76	0.71	0.71	0.72	0.74	0.64
LM (sp. er.)		0.69	1.43	6.5*	7.6**	0.14	0.95	0.48	0.28	0.21	0.41

log(pop) log population, *log(prod)* log labor productivity, *pi* residual of the regression of log population on first nature variables, *del* residual of the regression of log labor productivity on first nature variables, *LM (sp er.)* Lagrange Multiplier test for spatial error autocorrelation (for 2005, it is the LM-EL test), ** significant at 0.01, * significant at 0.05.

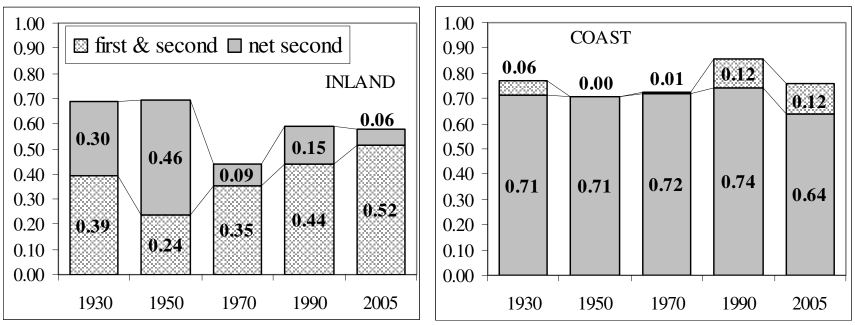

Fig. 12.5 Evolution of the impact of second nature on GDP density in 2 regimes

The influence of space on GDP density is certainly conspicuous. It leads to the so-called "two Spains", which are no longer split along the usual North *versus* South partition. In this case, we find a relevant geographical division: on the one hand, the coastal provinces plus Madrid, in which population and production focuses and on the other hand, an even more depopulated and sparse hinterland.

12.5.3 First and second nature joint effect on GDP per Area

We estimate how much of GDP per area variance can be explained jointly by gross first and second nature (V_f+V_s+V_{fs}). As in Eq. 12.9, we include a set of first nature indicators together with the net second nature variables (*pi*, *del*) as regressors. The joint importance of first and second nature is then measured by $R^2_{f+s} = \left(V_f + V_{fs} + V_s\right)\big/V$.

Thus from the set of the country's -physical and political- geography variables (Table 12.1) we must choose only those that are both related to the distribution of GDP density and not correlated with net second nature forces. As in Table 12.3, we pursue a general-to-specific modeling strategy in a first regression of GDP density on the complete set of 13 geography variables and the 2 net second nature variables. This procedure is repeated until all coefficients are all significantly different from zero at the 10% level. We find that only 8 geographic variables fulfill the cited requirements in all periods: regional capital, altitude, minimum temperature, average temperature, # days with below zero Celsius temperature, # days above 25º Celsius temperature, total rainfall and X-coordinate.

The regressions of GDP density on the complete set of 10 variables lead to high multicollinearity what inflate the determination coefficients. To avoid this problem, we opted for group the 7 physical geography variables (excluding regional capital) with factor analysis[12]. The rotated factors can be interpreted as follows: Factor 1 (*temp*) contains high scores of temperature variables, such as minimum/average temperature (positive), # days with below zero Celsius and altitude (negative). Factor 2 (*dry*) is related to dryness, with high scores in total rainfall (negative) and # days above 25º Celsius temperature (positive). Regarding factor 3 (*east*), it is mainly based on East-West orientation (X-coordinate). The regressions of GDP density on the 2 net second nature variables, 3 geography factors and the regional capital show much lower multicollinearity number, between

[12] Factors have been extracted using principal components and rotated with Varimax method.

1.941 (1950) and 2.040 (1930), well above the acceptable limit of 20/30 (Anselin 1995).

Again, we should test for the presence of endogeneity in the second nature variables since they could be simultaneously determined by GDP density. In this case, using the instruments shown in Table 12.5, we find that all second nature variables obtain significant DWH values except in the period 2005. Thus we apply IV method with the exception of in 2005, in which OLS is used (Table 12.8). As we can see, the joint contribution of first and second nature to GDP density remains constant (88-89%) across the Twentieth Century. That is to say, almost a 90% of the agglomeration pattern has been constantly explained by natural geography and agglomeration economies together, remaining the other 10% unexplained by these factors.

Once more, though there is no remaining spatial autocorrelation in the error terms, the spatial Chow test points out the problem of spatial instability in the coefficients. The estimation of the spatial regimes models illustrates the differences between the two subspaces. Thus the joint contribution of total geography is significantly lower in the inland provinces, much similar to Roos' figures for Germany (72%).

All coefficients have the expected signs. Results show the great importance of net second nature variables (population and productivity) on GDP density, which are significant for all the periods and spatial regimes. Among physical geography, temperature has the largest influence; e.g. in 1930, it increased the relative GDP density 68% reaching to 112% in 2005.

Regional capital is also a very influential variable and it obtains its main scores after 1990, from which Spanish regions ('autonomies') where officially recognized (34% in 1930, 101% in 2005). Similar to the German case, Spain is now a decentralized state with 17 regions that have a lot of legislative and executive power concentrated in the regional capital. This explains the growing influence of this variable on economic activity. Geographical orientation has also registered a rising tendency during the last century; i.e. Eastern locations are prone to record more GDP density than Western ones.

Regarding the spatial regimes, we find some interesting variations. In the group of inland provinces, regional capital is -by far- the most important determinant particularly from 1990, increasing GDP density by about 150%. It is followed by temperatures, since natural conditions differ considerably across the inland provinces, while Eastern orientation is not significant at all.

Table 12.8 First and second nature joint effect on GDP density

Period		1930		1950		1970		1990		2005	
Estimation		IV		IV		IV		IV		MCO	
Model		Basic	Spat. Reg.	Basic	Spat. Reg.	Basic	Spat. Reg.	Basic	Spat. Reg.	Basic	Spat. Reg.
Const.	Spain	-0.23**		-0.35**		-0.50**		-0.62**		-0.62**	
	Inland		-0.61**		-0.56**		-0.88**		-0.84**		-0.92**
	Coast		0.25		0.28		-0.01		0.11		-0.01
Capital	Spain	0.29*		0.54**		0.53**		0.71**		0.70**	
	Inland		0.47*		0.59**		0.68**		0.94**		0.90**
	Coast		-0.05		0.10		0.24		0.21		0.26
Factor 1	Spain	0.52**		0.49**		0.61**		0.73**		0.75**	
temp	Inland		0.24**		0.37***		0.33**		0.63**		0.55**
	Coast		0.25		0.08		0.38*		0.30*		0.41**
Factor 2	Spain	-0.31**		-0.35**		-0.37**		-0.23**		-0.17*	
dry	Inland		-0.07		-0.23*		-0.35*		-0.34*		-0.21
	Coast		-0.34**		-0.31**		-0.26**		-0.18**		-0.12
Factor 3	Spain	0.16*		0.19**		0.23**		0.21**		0.23**	
east	Inland		0.02		0.12		0.03		0.14		0.11
	Coast		0.15*		0.16**		0.22**		0.18**		0.23**
pi	Spain	0.70**		0.57**		0.75**		0.84**		0.96**	
	Inland		0.44		0.41*		0.54*		0.61**		0.59**
	Coast		0.86**		0.81**		0.77**		1.00**		1.08**
del	Spain	1.87**		1.99**		2.57**		2.52**		2.71**	
	Inland		1.43**		1.45**		1.57*		2.07**		2.09
	Coast		2.03**		1.82**		2.74**		1.93*		1.72
R-squared	Spain	0.88		0.89		0.88		0.89		0.88	
	Inland		0.74		0.75		0.63		0.72		0.66
	Coast		0.93		0.91		0.92		0.89		0.86
Multicollinearity #		2.04	4.84	1.94	4.49	1.99	4.68	1.94	4.56	1.94	4.53
Sp.Chowt		23.9**		22.3**		22.8**		28.1**		22.5**	
LM (sp. er.)		1.75	0.54	1.97	0.00	1.82	0.07	1.00	0.25	0.46	0.30

temp temperature, *dry* dryness, *east* West-East orientation, *pi* residual of the regression of log population on first nature variables, *del* residual of the regression of log labor productivity on first nature variables, *LM (sp.er.)* Lagrange Multiplier test for spatial error autocorrelation (for 2005, it is the LM-EL test), ** significant at 0.05, * significant at 0.01.

This outcome makes clear the situation of the progressively depopulated interior of the country. That is to say, location of production in the hinterland depends mainly on natural and political conditions. In these provinces agglomeration takes place mainly close to capitals and big cities, where the executive power and services concentrate producing employment and welfare. Concerning the coastal (plus Madrid) subspace, temperatures and dryness are the variables that exert the maximum influence on GDP density. In this area, longitude has gained more weight on GDP density illustrating the present advantage of the long Mediterranean urban areas with respect to the declining Cantabric-Atlantic axis (Le Gallo and Chasco 2008).

12.5.4 First nature net effect on GDP per Area

If we calculate the difference between the determination coefficient in Table 12.8 and 12.6 (Table 12.7 for spatial regimes) we obtain the importance of first nature alone (V_f) for the whole Spain: $V_f / V = R^2_{f+s} - R^2_{gs}$. In Fig. 12.6 we show the complete ANOVA decomposition for both the whole country and each of the spatial regimes. The total variation that can be assigned to the net effect of first nature ranks from 14% (in 1930) to 6-7% in 1990 and 2005, respectively. This result is almost coincident with Roos' who found a 7.1% for Germany. Nevertheless, it changes a bit when considering the 2 spatial regimes. Net first nature has had -in general-more influence on GDP density in the coastal provinces than in the inland, though they are leveling in both regimes at present (about 8-10%).

Independently of natural conditions, man-made agglomeration economies play an important role in the distribution of economic activity across Spanish territory. Nevertheless, this role is much significant in the coast than in the hinterland. In effect, since the coastal provinces share similar natural conditions, differences in GDP density are much due to interactions between economic agents among themselves than between agents and nature. In this subspace, first and second nature exerts basically a net influence. In contrast, the hinterland shows wider disparities in terms of physical geography -abrupt topography and continental weather- what confer more weight to mixed first-second nature; i.e. second nature forces are likely to overlay and to strengthen the forces of first nature. As a general rule, gross (net and mixed) first nature has increased its influence in Spain with time and it constitutes a 60% of GDP density distribution at present. However it is truer in the hinterland than in the group of higher GDP density provinces, in which first nature global effect has maintained practically stable during the last century in only a 22% of GDP per Area.

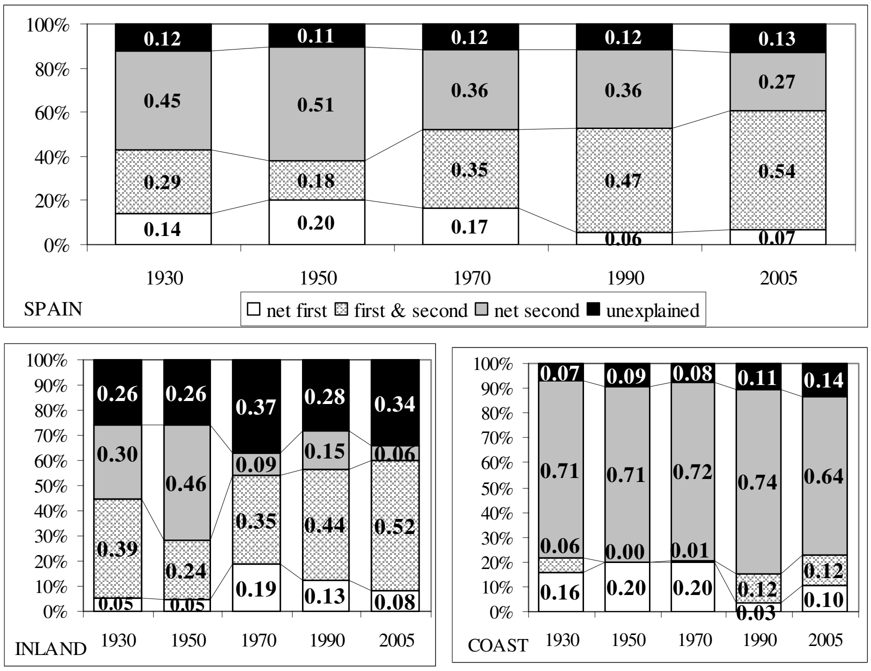

Fig. 12.6 Evolution of the variance decomposition of regressions in Table 12.8

Therefore, similar as in Gallup et al. (1999) Spanish economy is likely to bifurcate on two pathways. The coast plus Madrid metropolitan area experiences decreasing returns to scale in labor and high rates of population growth whereas the hinterland experiences more or less the opposite process. The two systems interact through ever-greater pressures on migration from the interior of the country to Madrid and the coast. This result demonstrates that when analyzing agglomeration in Spain, this dichotomous reality should not be avoided.

12.6 Conclusions

In this paper, we examine the influence of geographic features on the location of production in Spain. In other words, we quantify how much of the geographic pattern of GDP can be attributed to only exogenous first nature elements (physical and political geography) and how much can be derived from endogenous second nature factors (man-made agglomeration economies), in which first nature also operates as a mixed effect. Specifically we disentangle the contribution of each net component of geography with the aim of isolating the importance of first nature alone.

For this purpose, we follow the methodology proposed by Roos (2005) for Germany. He proposes to employ an analysis of variance (ANOVA) to infer the unobservable importance of first nature indirectly in a stepwise procedure. We also estimate how much of agglomeration can be explained by geography elements in a dynamic context, analyzing their evolution during the Twentieth Century. We demonstrate that results could be biased if some potential econometric questions are not properly taken into account; e.g. multicollinearity, relevant missing variables, endogeneity, spatial autocorrelation and spatial heterogeneity.

The main outcome of our study reveals that production is not randomly distributed across Spanish regions. In an exploratory spatial data analysis we find that GDP density has been historically bifurcated on two pathways, core and periphery, i.e. the coast plus Madrid metropolitan area and the hinterland, respectively. Even more, during the Twentieth Century this polarization has deepened leading to a new configuration of the so-called “two Spains”. Therefore we have estimated our models testing for and considering explicitly these spatial regimes.

Thus considering the Spanish territory as a whole we find that at most, 88% of GDP’s spatial variation can be explained by direct and indirect effects of geography during the whole period (1930-2005). These figures remain significantly far from those found in Roos for Germany (72%), pointing out the major role played by geography in Spain. After controlling for agglomeration economies and the interaction effect of first-second nature, the net influence of natural geography ranks from 20% (in 1950) to 6-7% nowadays.

However the influence of geography varies significantly from one spatial regime to the other. For example, in the group of inland provinces only a 56% of agglomeration is explained jointly by first-second nature forces, being the mixed effect quite strong, though with some variations in time (from 24% in 1950 to 52% in 2005). On its side, among the group of core provinces (coast plus Madrid), which share quite common physical geography characteristics, net second nature give the highest contribution to agglomeration, around 70% along the whole period.

In conclusion, independently of the interest of these findings for the Spanish regional analysis, we recommend taking into account spatial autocorrelation and heterogeneity explicitly in Roos’ methodology, since the core-periphery pattern is strongly present in most regions of the world. If they are not properly taken into account, results could be biased and rich information would be ignored.

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