RETURNS TO MATCHING: THE EFFECT OF SPATIAL INTERACTIONS IN LABOUR MARKETS

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ABSTRACT: Search and matching theories have become one of the main topics in labour market analysis. Constant returns to scale in the matching function have proved to be a necessary condition for the existence of a unique equilibrium rate of unemployment. Besides, increasing returns to scale in a group of economies could lead to multiple equilibrium, even when constant returns exist for all the economies as a whole. Some studies have pointed at this reason to explain the high level of dispersion in unemployment rates in the EU regions. In this paper, we assess the effects of spatial disaggregation when estimating returns to matching. If geographical externalities do not exert any influence on the matching process (or on the search effectiveness), estimation of returns to scale would be invariant to the level of disaggregation in the data. On the contrary, when unemployed and vacancies in other economies of the system act as potential inputs in the process of matching, and they are neglected in the empirical analysis, estimates of returns are downward biased. The empirical exercise deals with data for the Spanish economy. Applying panel data techniques, our results do not reject constant returns at the Spanish aggregate, whereas decreasing returns are observed for regions (NUTS II) and provinces (NUTS III). The hypothesis in the paper is confirmed given that when we allow interactions across regions/provinces constant returns cannot be rejected.

Keywords: Labour market, Matching Function, Panel data, Regions.

1. Introduction.

Following Pissarides (1992), models based on matching functions are used to explain the existence of unemployment as an equilibrium phenomenon. This equilibrium is reached when firms and workers maximise their respective objective functions subjected to matching and separation technologies. Under these conditions, it can be guaranteed the existence of a unique unemployment equilibrium rate where outflows from unemployment and inflows to unemployment are balanced.

Under matching models analysis, unemployment comes out as a result of two well defined facts: workers and job vacancies interacting in the market are both heterogeneous and subject to the existence of imperfect information. In both cases, this heterogeneity could be stated on their characteristics and/or their geographical location. In this sense, if agents accept a match, they are ready to assume the transaction costs originated in the comparison of different offers existing in the market. The matching function synthesises this process.

One the more important aspects that the literature has considered is whether the hypothesis of constant returns to scale in the matching function can be assumed empirically. This is because if the matching function exhibits increasing returns to scale, there is room for the existence of multiple equilibrium.

The main goal is toehold. First of all, we are interested in analysing how territorial aggregation of data may influence the estimation of returns to scale in the matching function. Secondly, we will test the existence of regional spillovers across regional labour markets. To do so, we use data on regional labour markets in the Spanish economy.

To attain these objectives, the paper is organised as follows. The second section briefly summarises, from a theoretical point of view, the basis of searching models: the matching function. Then, how previous literature has considered the relationship between the matching function and territorial analysis is discussed in section three.

After discussing some issues on data for the Spanish labour market in section four, results to the estimation of the Spanish matching function at different levels of territorial aggregation are presented. Finally, in order to study how spatial effects would influence the matching process in the Spanish case, section five tests for the presence of territorial spillovers and discusses their effects on the estimates of the returns to scale. We will finish the paper with the main conclusions. Section six concludes.

2. The base of searching models: the matching function.

The matching function settles down the flow of jobs formed each period as the result of the interaction of some aggregated variables. This flow will depend on the pool of variables that have some influence on the efficiency of the matching process as well as the number of agents operating in the market. From this viewpoint, the more important variables should be the number of workers searching for a job, as well as the number of job vacancies searching for a suitable worker. This matching process can be represented by the following expression:

$$H = H(S,V)\,, \tag{1}$$

where H represents the number of matches by period, S represents the number of workers searching for a job, and V, the number of job vacancies.

In order to understand how the matching process works, we will do the following assumptions:

- First of all, we will assume that the workers that are searching for a job are unemployed workers. Consequently, $S=U$, where U is the number of unemployed people.

- Function $H(\cdot)$ increases in both arguments: unemployed workers and job vacancies. Furthermore, we will suppose that $H(\cdot)$ is a Cobb-Douglas function where the elasticities describe the marginal effect of unemployed people and job vacancies on matches, and e^A represents the technology in the matching process.

$$H = e^A U^a V^b \ , \tag{2}$$

- If $H(\cdot)$ is homogeneous of degree one, that is to say, it shows constant returns to scale, it could be guaranteed that there exists a unique equilibrium unemployment rate (Pissarides, 1990).

- Unemployed workers and job vacancies that are finally matched are randomly selected from their respective pools (*U* and *V*). Consequently, the change between unemployed and employed states, as well as the change between a vacant job and filled vacancy, follow a Poisson process with rates $l_U = e^A H(U,V)/U$ and $l_V = e^A H(U,V)/V$, respectively.

If we apply logarithms to expression (2), we can obtain the following expression:

$$lnH = A + a\ lnU + b\ lnV \ . \tag{3}$$

Literature has taken into account different ways to analyse changes in efficiency through time. In this sense, efficiency can be modelled by a fixed constant during the period of analysis, as it has been expressed in (3), or be modelled by some economic variables that can show these changes in efficiency. The main factors that can influence these changes are the following ones:

- *Search intensity of unemployed workers and employees.*

- *Institutional changes on:*

- Unemployment benefits
- Some advantages in hiring specific unemployed workers like long-term unemployed people, youth unemployed, elder unemployed and/or unemployed women.
- Labour relationship structure.
- Firing costs.

- *Mismatch.* If an unemployed is specialised in a job (either in special sector or in a specific region of a country), this worker can have skills that may be far from those needed to develop a job that has been offered to him. Hence, given vacancies and unemployed, if they are not compatible, there will be fewer matches.

3. Effects of the level of territorial aggregation in data on the estimation of the returns to scale in returns to scale the matching function.

Returns to scale are important because the results obtained from a searching model are sensitive to the technology of the matching function (Kultti, 1998). Consequently, the literature has considered whether the hypothesis of constant returns to scale can be assumed empirically or not. Nevertheless, in spite of the fact that in the eighties this question was focused on their implications over the development of the Beveridge Curve (Blanchard and Diamond, 1989)[1], in the nineties the importance of returns to scale seem to focus on its implications for multiple equilibrium (Pissarides, 1990). In this sense, if the matching function exhibits increasing returns to scale, there is room for the existence of multiple equilibrium. As suggested by Profit and Sperlich (1998), heterogeneity in the matching process not only can affect efficiency, but also the marginal effects of both factors. Moreover, in spite of the fact that aggregated estimates can show constant returns to scale, the existence of increasing returns to scale in some of the regional labour markets could lead to different rates of unemployment in the long run.

Burda (1993) estimates the matching function for Western Germany and the Czech Republic by means of a panel regional of data. He obtained increasing returns to scale, with a low influence for vacancies in the matching process for the first case, and constant returns to scale for the second. These results are corroborated in Burda and Lubyova (1995) when the impact of active labour policies in the matching function for the Czech and the Slovak Republics are analysed. In this case, the authors obtain constant returns to scale in both economies in a dynamic matching function specification.

Burda and Profit (1996) are, as far as we know, the first ones in introducing regional externalities in the matching function. Their main result for the Czech Republic is that the lower the distance across locations of the labour market, the higher local returns to scale. However, in spite of introducing these spatial effects, they do not obtain increasing returns to scale.

In the same spirit, Burgess y Profit (1998) analyses the existence of spillovers for the United Kingdom labour market. The results show that they are relevant and decreasing returns to scale are obtained. These results care robust to changes in the specification of the model. The other main conclusion is that higher levels of unemployed in neighbouring regions increase the level of local vacancies posted, but decrease local unemployment outflows.

Data.

Before analysing the matching function for the Spanish economy, it is convenient to comment on data. Regional unemployment data are annual average data from the Spanish Labour Force Survey (*Encuesta de Población Activa, EPA)*. With respect to vacancies, some problems in the quantification of vacancies in Spain have to be pointed out. In Spain, the available information on vacancies is supplied by the Public Unemployment Service (*Instituto Nacional de Empleo*, INEM). The INEM registers two kinds of job offers: "named" job offers and "unnamed" job offers. The first ones are those in which firms notify a vacancy together with the name of the worker who is going to take the vacancy up. The last ones are those that firms want the INEM to search for suitable workers. Hence, for the Spanish case, we need to estimate the real vacancies existing in the labour market.

Antolín (1994) proposes a correction method for the Spanish case under the hypothesis that the INEM is less efficient than the market in the matching process. Thus, he considers that the duration of a vacancy is higher in the INEM than in the market. Antolin's correction method was proposed to correct the aggregated national vacancies. In this work we have used the same method under the additional hypothesis that the level of inefficiency INEM is similar in all the Spanish territory[2]

Finally, administrative vacancy data and those other variables needed to correct them, as well as hires, are provided by the INEM and its publication Employment Statistics (Estadística de Empleo).

4. Empirical matching function.

In order to analyse how different territorial aggregation of data can influence the estimates of returns to scale, we begin our analysis by means of the log-linear Cobb-Douglas matching function in (3)

In order to analyse how returns to scale can be influenced by the aggregation of regional data, we adapted expression (3) to the regional case as:

$$H_{it} = e^{A} U_{it}^{a} V_{it}^{b} , \tag{4}$$

where sub-index ***i*** indicates the territorial unity of analysis. In fact, regional samples to be considered are NUTS I (5 regions), NUTS II (17 regions) and NUTS III (50 regions)[3]. Adding a perturbance and in log-linear form:

$$\begin{aligned} &lnH_{it} = a\,lnU_{it} + b\,lnV_{it} + J_{it} \\ &\quad where: \\ &\qquad J_{it} = m_i + e_{it}, \\ &\qquad e_{it} \approx IID\left(0, s_e^2\right). \end{aligned} , \tag{5}$$

where h_{it}, u_{it} and v_{it} are regional hires, unemployment workers and job vacancies. m_i represents the efficiency of each region.

Results of estimation of the matching function are summarised in column [1] of Table 2 (Appendix III). As for regional disaggregated data the results can be observed in column [2] (NUTS I), column [3] (NUTS II) and column [4] (NUTS III). As it can be noticed, in all cases a random effects model for the regional unobserved effects is preferred as derived from Hausman tests (vs. fixed effects) and LM tests (vs. no regional effects)[4]. In this sense, as was pointed out by Baltagi (1995), each regional observation could be considered as a sample from the pool of all possible values that could be obtained for the variables under consideration.

A first glance at the results shows that the higher disaggregation in data the lower the estimation of the returns to scale. We cannot reject constant returns to scales for aggregated data, but they decrease to 0.889 when units under analysis are the Spanish provinces. Furthermore, we cannot reject the constant returns to scale with the usual significant levels in the NUTS I case, whereas for NUTS II, returns to scale are not rejected at 5%[5]. Consequently, these results can guarantee that if the Spanish matching function is well characterised by means of a Cobb-Douglas type function, returns to scale are not increasing. So, the possibility of a multiple equilibrium unemployment rate can be rejected for the Spanish case.

From Table 1, other interesting results can be obtained. First of all, the elasticity of matches with respect to unemployed workers increase to nearly 20%, whereas the elasticity of matches with respect to job vacancies drastically decrease between 50% and 75%. These results lead us to think that when we restrict labour markets to a more realistic local scope, the higher sensitivity of unemployed workers can be related with the low mobility of the Spanish labour force. However, the response of job vacancies is quite different. The wider the labour market where the job vacancy is searching for a suitable match, the higher the elasticity from matches to job vacancies.

When comparing these results to previous ones for the Spanish economy, we can find some interesting differences. Bell (1997) obtains an elasticity of matches with respect to unemployment of 0.88 and with respect to vacancies of 0.35. However, Castillo *et al.* obtain elasticities of 0.85 and 0.15, respectively. Our results are rather lower in the case of the elasticity with respect to unemployment, between 0.65 when aggregated data is used, and 0.76 when we use regional data.

5. Spatial interaction in regional labour markets: The Spanish case.

Once we have reached this point of the analysis, we considered that it could be interesting to analyse whether there are spatial interaction among different regional labour markets in Spain. In order to take into account these interactions, we analysed three possibilities to capture this kind of effect for the cases of the NUTS II and NUTS III samples.

The idea is that hiring in region ***i*** is a function of unemployment and vacancies in some other regions, besides the ones within the region. Then, the amplified matching function can be defined as[6]:

$$H_{it} = e^{A} U_{it}^{a} V_{it}^{b} UR_{it}^{g} VR_{it}^{d}\,, \tag{6}$$

where UR_{it}^{g} and VR_{it}^{d} capture the unemployment and vacancies effects of the other regions on the local labour market; ***g*** and ***d*** represent the elasticities of hires of region ***i*** with respect to unemployment and vacancies in the other regions. We could wonder whether vacancies from neighbouring regions have to be introduced in the local matching function as an input. Obviously, this question does not depend on the approach that has been taken for the spatial effect. In this sense, it can be argued that the omission of this variable could bias the estimates of the elasticity of local matches with respect to local unemployment. This could be due to the fact that local unemployed workers can search for a suitable job in other markets outside local regions which can be matched with job vacancies available in other labour markets of the territory. To capture these effects, we considered three possible alternatives:

- *Neighbours:* In this case, we only include unemployment and vacancies from geographical contiguous regions. Consequently, UR_{it} and VR_{it} can be defined as:

$$UR_{it} = \sum_{j \in J} U_{jt} \quad and \quad VR_{it} = \sum_{j \in J} V_{jt} \ , \tag{7}$$

where ***J*** denotes the subset of regions adjacent to ***i***.

- *Inverse of the distance:* In this case, unemployment and vacancies of the rest of regions are included but weighting by the distance between each region and region ***i***. In this case, UR_{it} and VR_{it} are obtained as:

$$UR_{it} = \sum_{j \neq i} \frac{1}{d_{ij}^2} U_{jt} \quad and \quad VR_{it} = \sum_{j \neq i} \frac{1}{d_{ij}^2} V_{jt} \ , \tag{8}$$

where $\boldsymbol{d_{ij}}$ is the distance between region ***i*** and ***j***.

- *Upper Territorial Unity:* In this case, we considered unemployment and vacancies from upper territory unit (in NUTS III it corresponds to NUTS II, and in NUTS II it corresponds to NUTS I) excluding of those from the region ***i***. Consequently, UR_{it} and VR_{it} will be computed as:

$$UR_{it} = \sum_{\substack{j \in J \\ j \neq i}} U_{jt} \quad and \quad VR_{it} = \sum_{\substack{j \in J \\ j \neq i}} V_{jt} \ , \tag{9}$$

where ***J*** denotes the subset of regions within the wider regional division. In this case, we have omitted from the analysis NUTS III that consist of only one region of type NUTS II. These regions are, Asturias, Baleares, Cantabria, Madrid, Murcia, La Rioja and Navarra.

Adding a disturbance to If we apply logarithms to expression (6) we obtain:

$$
\begin{aligned}
& lnH_{it} = a\,lnU_{it} + blnV_{it} + glnUR_{it} + dlnVR_{it} + J_{it} \\
& \quad where: \\
& \qquad J_{it} = m_i + e_{it}, \\
& \qquad m_i \approx IID\left(0, s_m^2\right) \quad and \quad e_{it} \approx IID\left(0, s_e^2\right).
\end{aligned}
\quad , \qquad (10)
$$

where $m_i \approx IID\left(0, s_m^2\right)$ indicates that a random effects model is estimated given the results that we obtained in the previous analysis.

Table 3 (Appendix III) shows the estimates of expression (10) for NUTS II and NUTS III. For NUTS II, within the region returns to scale $(a + b)$ do not substantially differ from those without spillovers. Moreover, when we consider the effect of the neighbours (column 1), as well as the inverse of the distance (column 2), the hypothesis of local returns to scale cannot be rejected. For these cases, elasticities of both factors are very similar to the ones previously discussed. Nevertheless, when the spatial effect is taken into account as an upper territorial unit effect (column 3), the constant returns to scale hypothesis is rejected. However, it has to be pointed out that in this case, local vacancies are not significant whereas those in the other regions are. Obviously, this is an unlikely result.

In all, we can conclude that spillovers across labour markets at NUTS II level in Spain are not significant. The results are more interesting in NUTS III. First of all, it has to be pointed out that the constant returns to scale hypothesis is rejected in all three cases. However, when spatial effects are introduced, this hypothesis is not rejected and the results show that the spatial effects are relevant.

Another interesting result that can be obtained from Table 2 is that the unemployment level from other regions is not important in the local matching process. Thus, the results seem to corroborate the view that we had before analysing spatial effects: mobility in Spanish labour market is very low. However, as increases in vacancy jobs in other regions have a positive influence in local matches, we can denote a spillover effect of economic activity through labour market.

To sum up, we can say that the results obtained are very similar to those from Castillo *et al.* when we analyse NUTS II, but elasticity from matches with respect to unemployment is a bit lower. These results do not change when we study the matching function with disaggregated data for NUTS III.

6. Conclusions.

In the present paper we have analysed the effect of territorial disaggregation of data the estimation of returns to scale in the matching function for the Spanish case. The results show that there are some important differences in the estimates of the returns to scale, as well as in the role of unemployment and vacancies in the process of matching. In all, three main points could be raised. First of all, returns to scale decrease as much as 20% when data for provinces is considered. Secondly, we can reject the null hypothesis of constant returns to scale for such territorial units. Thirdly, the elasticity from matches with respect to unemployment increases almost 20%, whereas with respect to vacancies it drastically decreases between 50% and 75%. These results could be related to a higher competence among unemployed when labour markets are better bounded. However, vacancies work differently. The wider the labour market, the larger the estimate of the elasticity. This could be due to the fact that competence among vacancy jobs when searching for suitable workers is higher in wider markets.

Implications out from these results could be rather interesting. First of all, higher elasticities from matches with respect to unemployment, advice of the importance fighting against the low search intensity of unemployed more than the existence of a lack new jobs. This is even more evident when we consider estimates from a more local labour market. Furthermore, in this case, our results are closer to the ones in other European economies, where the estimate of elasticity for unemployment is around ¾, while for vacancies is around ¼.

With respect to the kind of returns to scale of the matching function for the Spanish case, we can guarantee that if the Spanish matching function is well characterised by a Cobb-Douglas function, there seem to be no room for increasing returns to scale. The fact that the returns decrease with the regional disaggregation of data agrees with some other empirical literature on this issue, (López-Tamayo ,2000).

Once we have analysed the effects of different regional data aggregation on the matching function, we have ascertained whether there are spatial interactions in regional Spanish labour markets or not. The results show that the omission of spatial spillovers in the estimation of the matching function can bias the results downwards. This can be noticed when we omit the spatial effects in NUTS III analysis obtaining decreasing returns to scale. If we introduce spatial effects, the hypothesis of constant returns to scale cannot be rejected. The more disaggregated the analysis, the more important the effect is. Consequently, it seems that when the labour market selected is a more realistic one, the spatial spillovers are more important, encouraging us to go deep into this research line.

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[1] López-Tamayo, J. and Suriñach, J. (1999) analyse Beveridge Curve for the Spanish case.
[2] With respect to the correction methodology, see appendix I and Antolín (1994).
[3] See appendix II fo a description of territorial units in Spain.
[4] See for instance Baltagi (1995), Green (1993).
[5] See López-Tamayo (2000) for a survey of the effects of territorial disaggretation in the estimates of the matching function.
[6] It has to be pointed out that this expression is a reduced form of: $H_{it} = e^{A}\left(U_{it} \cdot UR_{it}^{t_U}\right)^{a}\left(V_{it} \cdot VR_{it}^{t_V}\right)^{b}$, where $g = t_U a$ y $d = t_V b$.

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APPENDIX I (Variables).

h_{pt}: logarithm total hires from the region *p*. Estadística de Empleo (Ministerio de Trabajo and Seguridad Social)

u_{pt}: logarithm of the unemployment from the region *p*. Encuesta de Población Activa.(INE).

v_{pt}: logarithm of the corrected vacancies from the region *p*.(Antolín, 1994). Estadística de Empleo (Ministerio de Trabajo and Seguridad Social) and Encuesta de Población Activa (INE).

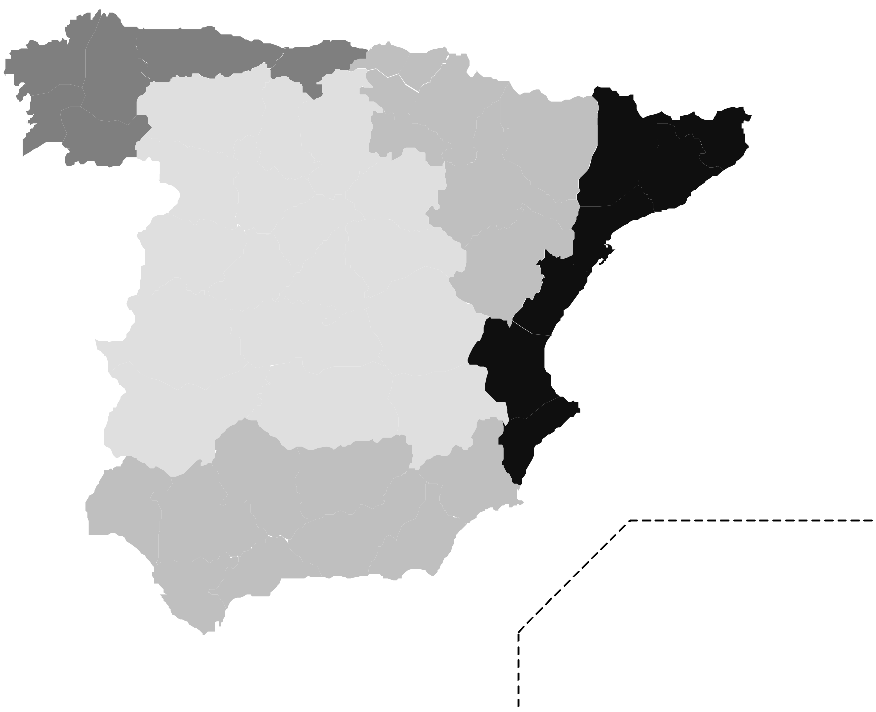
$$V_{it} = \left[1 + k\,\frac{OUT_{it}^{\ N}}{OUT_{it}^{\ U}}\right] V_{it}^{\ A}$$

Where:

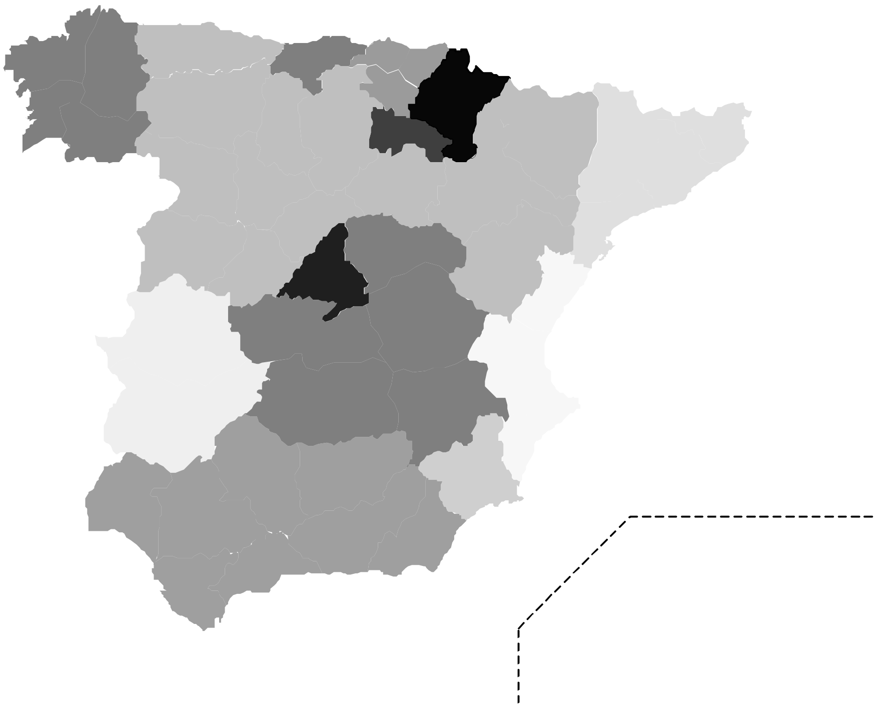
V_{pt}	corrected vacancy of the region *p*.
k	relative efficiency factor from Public Unemployment Service to market. Estimated in 0.25.
$OUT_{pt}^{\ N}$	named job offers from the region *p*
$OUT_{pt}^{\ U}$	generic job offers plus job offers removed from region *p*.
$V_{pt}^{\ A}$	public vacancies of the region *p*.(Offers not covered at the end of the month).
L_{pt}	labour force from the region *p*.

APPENDIX II Spanish Territorial Distribution.

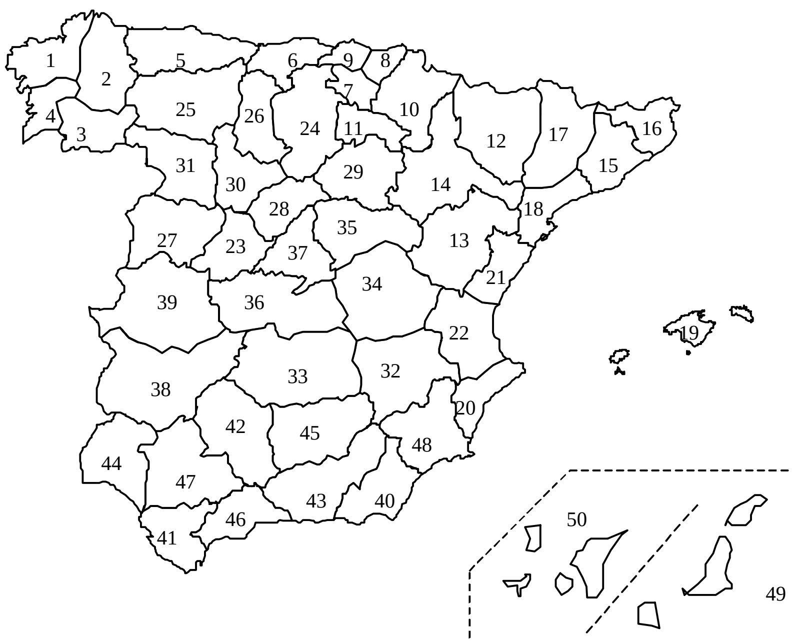
Map A. NUTS I Spanish Regions



Map B. NUTS II Spanish Regions.



Map C. NUTS III Spanish Regions



Legend of Maps A, B and C.

Map A	Nuts I	Map B	Nuts II	Map C	Nuts III
	Northwest		Galicia	1	La Coruña
				2	Lugo
				3	Orense
				4	Pontevedra
			Asturias	5	Asturias
			Cantabria	6	Cantabria
	Northeast		País Vasco	7	Alava
				8	Guipúzcoa
				9	Vizcaya
			Navarra	10	Navarra
			La Rioja	11	La Rioja
			Aragón	12	Huesca
				13	Terruel
				14	Zaragoza
	East		Cataluña	15	Barcelona
				16	Gerona
				17	Lérida
				18	Tarragona
			Baleares	19	Baleares
			Comunidad Valenciana	20	Alicante
				21	Castellón
				22	Valencia
	Center		Castilla-León	23	Ávila
				24	Burgos
				25	León
				26	Palencia
				27	Salamanca
				28	Segovia
				29	Soria
				30	Valladolid
				31	Zamora
			Castilla-La Mancha	32	Albacete
				33	Ciudad Real
				34	Cuenca
				35	Guadalajara
				36	Toledo
			Madrid	37	Madrid
			Extremadura	38	Badajoz
				39	Cáceres
	South		Andalucía	40	Almeria
				41	Cádiz
				42	Córdoba
				43	Granada
				44	Huelva
				45	Jaén
				46	Málaga
				47	Sevilla
			Murcia	48	Murcia
			Canarias	49	Las Palmas
				50	S.C. De Tenerife

APPENDIX III Results.

Table 1. Estimates of the mismatch function (1978-1996).

	Spain [1]	NUTS I [2]	NUTS II [3]	NUTS III [4]
Cte	1.121	0.832	1.247	1.139
	(2.135)	(0.802)	(0.282)	(0.126)
α	0.651	0.777	0.756	0.778
	(0.335)	(0.146)	(0.065)	(0.034)
β	0.447	0.235	0.161	0.111
	(0.185)	(0.081)	(0.035)	(0.012)
$\alpha+\beta$	1.097	1.012	0.918	0.889
H_0: $\alpha+\beta=1$	[0.691]	[0.545]	[0.096]	[0.000]
#	19	95	323	950
σ	0.356	0.423	0.455	0.441
F	[0.000]	[0.000]	[0.000]	[0.000]
H	----	[0.859]	[0.308]	[0.649]
LM	----	[0.000]	[0.000]	[0.000]

Dependent variable: logarithm of total hires.
Standard error between parenthesis. p-value between brackets. Regional effects omitted.
(σ) standard error. (LM) Lagrange multiplier test. Random effects vs. Pool
(H) Hausman.test: Random effects vs. fixed effects.

Table 2 Estimates of the matching function with spillover effects (1978-1996).

	NUTS II			NUTS III		
	Neighbours	The inverse of the distance	Upper Territorial Unity	Neighbours	The inverse of the distance	Upper Territorial Unity
	[1]	[2]	[3]	[4]	[5]	[6]
Constant	1.351	0.843	0.651	0.759	2.786	0.563
	(0.367)	(0.402)	(0.388)	(0.230)	(0.268)	(0.206)
α	0.763	0.754	0.716	0.682	0.746	0.665
	(0.067)	(0.067)	(0.072)	(0.039)	(0.036)	(0.040)
β	0.160	0.165	0.049	0.061	0.052	0.066
	(0.035)	(0.035)	(0.041)	(0.053)	(0.014)	(0.015)
$\alpha+\beta$	0.923	0.919	0.765	0.743	0.798	0.732
H_0: $\alpha+\beta=1$	[0.130]	[0.113]	[0.000]	[0.000]	[0.000]	[0.000]
γ	-0.034	0.124	0.083	0.083	-0.053	0.167
	(0.063)	(0.088)	(0.080)	(0.053)	(0.054)	(0.050)
δ	0.029	-0.139	0.189	0.141	0.241	0.081
	(0.057)	(0.090)	(0.051)	(0.027)	(0.035)	(0.029)
$\alpha+\beta+\gamma+\delta$	0.918	0.904	1.037	0.968	0.986	0.979
H_0: $\alpha+\beta+\gamma+\delta=1$	[0.154]	[0.078]	[0.742]	[0.368]	[0.698]	[0.285]
#	323	323	323	950	950	817
σ	0.455	0.453	0.437	0.428	0.427	0.428
F	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LM	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Dependent variable: logarithm of total hires.
Standard error between parenthesis. p-value between brackets. Regional effects omitted.
(σ) standard error. (LM) Lagrange multiplier test. Random effects vs. Pool
(H) Hausman test: Random effects vs. fixed effects.