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# URBAN AND INDUSTRIAL AGGLOMERATION: EFFECTS ON REGIONAL LABOUR MARKETS

DE CASTRIS MARUSCA[1], PELLEGRINI GUIDO[2]

## SOMMARIO

The "size" effect, related to the dimension of regional labour market, is often attributed to the presence of productive specialization area and industrial agglomeration. In this paper, we study separately agglomeration effects due to high concentration of population and those due to firm's clusters or high presence of employees. We estimate the correlation between unemployment and agglomeration at disaggregated territorial level (Nuts 2), conditioning for covariates related to demographic, economic and geographical effects, including those related to core-periphery approach. Moreover, regional labour markets are spatial correlated within contiguous areas: we carefully model the presence of spatial correlation by a spatial lag model. We expected that the size effect is lower in Europe than in USA. Nevertheless, effects related to agglomeration of firms could be higher than effects related to agglomeration of people. Early results show that urban agglomeration in Europe has a negative effect on employment; the results are opposite for industrial clusters, where the presence of firm's agglomeration has a positive effect on labour markets.

[1] Department of Political Institution and Social Science, Roma Tre, University of Rome
Via Gabriello Chiabrera, 199 – 00145 Roma, e-mail: m.decastris@uniroma3.it.
[2] Department of Economic and Social Analyses, Sapienza, University of Rome, Piazzale Aldo Moro, 5 - 00185 Roma, e-mail: guido.pellegrini@uniroma1.it.

## 1 Introduction

The aim of the paper is to assess the effects of urban and industrial agglomeration on labour markets in European regions. OECD (2002) report highlights the difference in geographical structure of population and employment between Europe and USA, pointing out the different degree of agglomeration and the different overlap between urban concentration and industrial concentration in both areas. Are the differences important in explaining the different levels of unemployment among regions in the two areas? The European labour market is characterized by the persistence of high average unemployment rates since the 1970s, after the oil shocks. During the 1980s and the 1990s the unemployment rates increased further and nowadays the level of unemployment is still high compared to the beginning of the seventies. The initial increase in unemployment in Europe was primarily due to adverse and largely common shocks, from oil price increases to the slowdown in productivity growth. The fast raise led most countries to institutional changes, in order to reduce the level of unemployment by employment protection, and to reduce unemployment social distress by more unemployment insurance (Blanchard, 2006). However, differences in the istitutional enviroment clearly affect the observed geographic variability of unemployment rates across European countries. The literature suggests that the regional distribution of unemployment rate in Europe is also affected by barriers to job mobility, mismatching between supply and demand of heterogenous skills, differences in sectorial structure and composition.

Heterogeneity across regions depends, at the first glance, by heterogeneity of unemployment rates across countries. Differences between contries explain around the 40% of unemployment rate total variance. Heterogeneity is more marked today then in the past (Blanchard, 2006). Unemployment level is relatively low (lower than the United States) in many countries like the Netherlands, Denmark and Ireland. Regions with high levels of unemployment are mainly concentrated in the East of Germany, in the South of Italy and Spain, and in some urban areas like Bruxelles, Berlin, Hamburg.

Literature has investigated dynamics and structure of regional unemployment. Bertola (2000) shows that large and persistent unemployment differentials across European regions can be attributed to low labour mobility and rigid wages. In the last decade, the thickness of labour market has been recognized as a source of positive externalities, that increase the labour mobility and the trasmission of wage signals. The positive effect is explained by the presence of clusters of firms and workers in the same area, that facilitate matching in local labour markets (Glaeser and Maré, 2001; Ciccone, 2002). In the same direction various economists have been discussed the role of agglomeration externalities in the labour market. A study by Gan and Zhang (2006) for United States argues that geographic variability and fluctuations of the unemployment rate are also related to agglomeration externalities, linked to thick labour markets; they show a negative significant correlation between unemployment rate and city size in the USA. Recently Bleakley and Jeffrey (2007) show that, on average, workers change occupation and industry less in areas with high density population where people find higher wages, natural locational advantage such as a convenient transportation node, lower transports costs, increase of service economy. They say that "…the rate of occupational and industrial transitions is indeed lower on average in thicker labor markets". Brülhar and Mathys (2008) study agglomeration effects on labour productivity for a panel of European regions of 20 Western and Eastern European Countries. They find that agglomeration effects appear very strong in the EU's new member states.

A common feature of most of the studies above is that they investigate the functioning of labour market without considering the spatial dimension of regional labour market disparities. Few studies have explicitly considered the spatial dimension of regional labour markets.Overmann and Puga (2002) indicate the presence of unemployment rates homogeneity across neighbouring areas rather than across regions of the same country. In this way the neighbouring effects is much more important than the productive or skill structure in the spatial association of unemployment. Niebuhr (2003) considers spatial dependence a central feature of the unemployment differentials of European regions and the results point to different forms of spatial interaction that affect change in regional unemployment such as commuting, migration or interregional trade. López-Bazo et al. (2005) verify the existence of large differentials in unemployment rates across the Spanish provinces and find that unequal distribution of amenities is the main reason of spatial inequalities in unemployment rates.

The geografical location of people and firms are different in Europe with respect to United States. Usually, large urban agglomerations in Europe are not the result of the development of business agglomerations, especially large ones, as has often happened in the United States, but the result of an urbanisation process which brought in many people from the agricultural sector, or their children, to look for a better life in urban areas where the growth of the service sector, public as well as private, offered better salaries. Morover, in Europe (especially in France, Italy, Spain), we find several agglomerations of firms in intermediate zones, between rural and urban zones, where areas with a high density of small and medium-sized firms, often manufacturing, are also located. Some of these areas, featuring specialised sectors called "industrial districts," have had particularly positive results in terms of employment and growth. The lack of a clear bipolarity between urban and rural areas indicates the presence of agglomerations of firms with different characteristics, size and above all, location, from agglomerations of people. In USA and Canada, urban agglomeration and firm's agglomeration generally overlap. This can be an explanation of why Gan and Zhang in their study do not discriminate for the nature of agglomeration (firms or people).

Sometimes, urbanisation has either broken or fragmented the information chain which matched labour supply and demand where efficient market institutions were missing. Actually, the sign of the effects of agglomeration on the intensity of job searching and matching results is not clear (Di Addario, 2005). Higher congestion and the unravelling of "close" social ties can increase the costs of searching and thus reduce the intensity and the results of the search. On the other hand, as Gan and Zhang (2006) stress, positive effects can come from thick markets, with a high density of workers and firms, which reduces the cost of contacts in terms of the distance between supply and demand or the cost of collecting information. Higher salaries in urban areas also increase the intensity of searches. The overall net effect will thus depend on the level of the thick market externalities as compared to the negative effects of congestion.

The difference between the geografical location of people and firms between US and Europe is presented in Table 1. We confront here two basic different concept of economic agglomeration: i) agglomeration across urban areas, basically measured by city size (population); ii) agglomeration across industrial clusters, measured by cluster size (employment or plants number). The differences in the location pattern of economic activity with respect to the urban areas can be captured by the differences in the measurement of the empirical counterpart of the two concepts. An easy way to perform a cross country comparison can be based on a simple dissimilarity index for a country k ($ID_k$):

$$ID_k = \sum_i \left| q_{pop} - q_{emp} \right|_i \qquad (1)$$

where $q_{pop}$ is population share by area i and $q_{emp}$ is employment share by area $i$ in country $k$.
An indicative analysis for EU regions (NUTS2) and US counties emphasizes the difference between the two areas (Table 1). As expected, the dissimilarity between the population

location and the industrial location is low in United States, higher in Europe.

*Table 1 Dissimilarity index in USA and Europe*

| Countries | Number of regions (a) | Average population by region | Average area by region (thousand square km) | Dissimilarity index (all sectors) (b) | Dissimilarity index (manufacturing) (c) | (b/a) | (c/a) |
|---|---|---|---|---|---|---|---|
| USA | 172 | 1,657,522 | 20,566 | 0.0476 | 0.195 | 0.0003 | 0.0011 |
| Italy | 103 | 562,387 | 2,925 | 0.1549 | 0.414 | 0.0015 | 0.0040 |
| Germany | 49 | 1,680,428 | 7,285 | 0.0656 | 0.167 | 0.0013 | 0.0034 |
| France | 96 | 616,592 | 5,666 | 0.0997 | 0.194 | 0.0010 | 0.0020 |
| UK | 133 | 442,390 | 1,833 | 0.0757 | - | 0.0006 | - |
| UE-12 | 110 | 3,103,300 | 20,401 | 0.1239 | - | 0.0011 | - |

*Source:* Own estimate on OECD and Eurostat data. The data are collected in the years from 1996 to 2001.

The paper intends to highlight agglomeration effects on the local unemployment rate. The contribution of the paper is strictly empirical: we propose to disentangle urban and industrial cluster agglomeration effects, by controlling for a wide set of variables, basically related to sectorial and dimensional shocks, in order to highlight the total “size” effect in the labour market.

The study is based on a cross section analysis applied to a fine territorial grid, composed of 105 regions at NUTS II level (Nomenclature of territorial units for statistics) over 12 European Union countries (UE12). We estimate the relation between unemployment and the specific characteristics of European labour market including agglomeration effects for European regions, contrasting the results with those for the US. We control for the presence of sectorial shocks (differences in sectorial structure can affect the level of unemployment rates even in the presence of nationwide sectorial shocks), and also for the presence of positive or negative covariance among sectors in the same area, and also for specific shocks concerning the size of firms. Adjusting the system for the effects of sectorial and size shocks, which will be persistent due to reduced mobility, as well as those relating to geographic structure, geographical dependency and policy interventions, the results of our analysis stresses the presence of negative and significant urbanisation externalities. The result stands up to different specifications. We obtain, instead, positive effects concerning the geographic agglomeration of firms, and their thickness, in a specific area. Finally, the model distinguishes the negative effects of urban agglomerations (in terms of population density) from positive firm's agglomerations (in terms of density of manufacturing employment).

## 1. Methodology

The methodological contribution of the study is the identification of a "size" effect in the labour market of European regions by an econometric model. Our empirical specification assumes that the regional unemployment rate (in the 2006) depends on specific demographic and economic features of the areas and on agglomeration effects. Our starting point is a model based on a reduced form in cross-sectional context3:

$$u_i = a + b^*(\text{covariates})_i + e_i \qquad (2)$$

where $u_i$ is the unemployment rate, $i$ is the i-th regions at Nuts II level, the covariates are composed by variables representing the sectorial and diversification structure, the development level of the region, the incidence of low educated employment and dummy variables for countries fixed effects. As a proxy of the size of the market we use variables related to the level and to the density of population, employment; as usual, in literature, we transform all size variable using a logarithmic operator. The reason is that the size is a non stationary variable (in our sample) but the unemployment rate is stationary (in the long run), and the logarithmic transformation gives less weight to the larger values. $\varepsilon_i$ is an error term assumed *iid* as a first approximation. In presence of spatial dependence OLS leads to inefficient estimators and

[3] The model of Gan and Zhang (2006) is based on a panel data, and therefore it includes also time and random effects.

unreliable statistical inference. Therefore we have adopted spatial econometric methods and we estimate a model specification that considers the presence of spatial autocorrelation.

The spatial econometrics in the model is based on a spatial contiguity matrix with (*nxn*) elements $w_{ij}$ representing the topology of the spatial system of the 105 regions. We tested for the presence of spatial correlation in model residuals. The results clearly indicate a strong spatial correlation across area. In this case the fundamental problem of this set-up is that of identifying a set of control variables able to detect geographical variability excluding the effects of size, which can subsequently be estimated with reasonable accuracy. As described above, the control variables must take into account sectorial shocks as well as the sectorial structure and risk level (in terms of sectorial covariance) of the industry and demographic composition. [4]

We tested several model specifications including different explanatory variables to examine the effect of urban and industrial agglomeration on the geographical distribution of unemployment conditioned to the availability of the data. We add "size" variables, like urban agglomeration and industrial agglomeration, and test their statistical significance.

The model that takes in account the size effects is therefore:

$$u_i = a + b^*(\text{covariates})_i + d^*(\text{size})_i + e_i \qquad (3)$$

### *1.1 Data and spatial weights matrix*

The empirical analysis of the model was carried out on a regional data set based on the EU12. Our data are extracted by the last version of the OECD-STAT database. The information we use are related to 105 regions at NUTS II level (Nomenclature of territorial units for statistics) over the 12 European Union countries: Belgium (3 regions), Germany (11 regions), Denmark (3 regions), Spain (17 regions), France ( 22 regions), Greece (4 regions), Ireland (2 regions), Italy (21 regions), Luxembourg (1 Region), Netherlands (4 regions), Portugal ( 5 regions) and United Kingdom (12 regions).

[4] These variables are usually present in the specification adopted by Gan and Zhang.

In literature we find strong evidence that agglomerations operate at relatively small spatial scale, but we assume, as in other studies, that proximity effects can be captured by the analysis at regional level. The problem is that when the spatial grid is wide enough, the mismatch between area of residence and area of work has a low probability to happen (Brunello, Gambarotto, 2004). Therefore, if the area is too large, apart from demographic differences, the population share by area is equal to the employment share by area. However, our hypothesis, confirmed by the data, is that the differences between the two shares are relevant in order to identify agglomeration of people and agglomeration of firms.

Heterogeneity of unemployment rate can be shown by the distribution represented using Epanechnikov kernel and a window of 30 observations (Fig. 1). The kernel distribution is unimodal (the mode of the variable is 3,7%) skewed to the right, with few regions with an unemployment rate greater than the 15%.

The choice of the spatial matrix is central in the specification of the spatial autocorrelation model. The spatial weights matrix cannot be constructed starting from a simple contiguity matrix, otherwise the weight matrix will include rows and columns with only zeros due to the presence of islands. We have chosen to use a spatial matrix based on the binary contiguity of the regions. However the definition of contiguity is based on distance: two regions are contiguous in our scheme if the distance among the main towns is lower than 300 kilometres.

In our work we use an economic definition of contiguity: by this specification, regions that are determined to be 'next to another' by virtue of be closer enough have a '1' entered in the correspondent cell of the matrix, where those that are not neighbours have a zero. From our point of view this should be sufficient to capture the basic economic spatial interaction that we consider in our model. The cut-off point is arbitrary but this choice guarantees that every single region should be connected to at least another region. However, we assume that interactions among regions more distant than 300 kilometres are negligible.

The resulting weight matrix is symmetric with zero along the main diagonal. The matrix is standardized so that each row sum to unit. More precisely, we use the great circle distance between regional main towns defined as:

$$w_{rk} = 0 \text{ if } r=k, \ \forall r$$

$$w_{rk} = 1 \quad \text{if } d_{rk} \leq h \qquad \text{if } r \neq k$$

$$w_{rk} = 0 \quad if\, d_{rk} > h \quad if\, r \neq k$$

where $h$ is equal to 300 kilometres.

Our dependent variable is the unemployment rate of each region in the year 2006.

The covariates that consider economic, demographic and social features of the area are the following:

1. a measure of the output of regional economy: gross domestic product per capita that increases the scale of differences between regions;

2. a proxy of average human capital of the workforce in each region: the share of labour force with primary education;

3. countries dummies: to isolate unobservable fixed effect for each country;

4. a proxy to capture the structural aspects of the region: the share of agriculture employment in the year 2004.

Because the dependent variable, unemployment rate, is measured for the year 2006, we take values of the covariates for the period 2001–2004 to avoid endogeneity. In line with the literature we consider a set of additional control variables for further differences across regions.

First, a variable regarding the effect of regional sectorial structure (*Indcom*) considers both the nationwide industry shocks and the sectorial structure of each region. It has been calculated considering 6 industries ( groups of 1 digit Ateco by tipology: 1. A,B ; 2. CDE ; 3. F; 4. GHI; 5. JK; 6. LP ). The variable is obtained in each region as the sum of the products of employment share $q_{jr}$ in sector $j$ respect to employment of the region $r$ in 2001 by the nationwide employment growth rate in that sector $\Delta_j$ in the period 2001-2005.

Let j be the economic sector:

$$Indcom_r = \sum_{j=1}^{6} q_{jr} * \Delta_j \qquad (4)$$

Its sign is predicted to be negative, since if the changes in sectors with positive shocks is greater than that of sectors with negative shocks, there is a net positive effect on employment in the region.

A different effect regards the presence of sectorial diversification. Excessive productive specialisation, in fact, lowers the capacity to compensate for sectorial shocks and increases the risk of unemployment. This effect is detected in the model through a risk variable that represents the risk of sectorial diversification, meaning the presence of a correlation between sectors making up the economy of the local system. We follow the idea of Neumann and Topel (1991), the sectorial diversification index was obtained multiplying the employment share $q_{jr}$ for the covariance matrix $\Omega$ (size 6x6) of the nationwide sector specific shock to take in account the different variability of the employment within the sector of the share of employed people at a national level in the 2001:

$$Risk_r = q_r^{'}\Omega\ q_r \qquad (5)$$

Considering the 'size' variables, we measure the urban agglomeration as the popolation density in the region or the level of population in the year 2003.

We measure also the industrial agglomeration as employment density or employment level in 2005 in the working area, moreover the employment density in the manufacturing sector in the year 2001.

### *1.2 Presence of spatial dependence*

The presence of a spatial pattern in the unemployment distribution can be detected by the analysis of spatial correlation, a standard statistical measure of spatial interactions. The indexes of spatial autocorrelation measure the influences of economic and social phenomena in the space. In other word, the objective is to evaluate if an economic variable (X), observed in two (geographically) neighbouring areas, assumes on average similar or dissimilar values. The most used index *Im* of spatial correlation, defined by Moran, has the following expression:

$$I_m = \frac{n\sum_i \sum_j w_{ij}\left(x_i - \bar{x}\right)\cdot\left(x_j - \bar{x}\right)}{\left(\sum_i \sum_j w_{ij}\right)\sum_i \left(x_i - \bar{x}\right)^2} \qquad (6)$$

Where n is the number of observations; $w_{ij}$ (binary weight) is one element of the contiguity symmetric matrix $[w_{ij}]$ with null diagonal $(w_{ii} = 0)$ and its value is equal to one if the area i and area j are contiguous, zero otherwise; $x_i$ are the values of the variables X for the $i^{th}$ unit.

The correlation analysis by Moran's *Im* index in the regions of EU12 is presented in table 2. In general, the distribution of unemployment as well as gross domestic product across NUTs II is clearly positively spatial correlated. We find also a positive and statistically significance spatial correlation of sectorial composition and low education. The spatial correlation of low education is larger than the spatial correlation of unemployment and gross domestic product.

*Table 2 Spatial autocorrelation of covariates.*

| *Variables* | *I* | *E(I)* | *s.d.(I)* | *Z* | *p-value** |
|---|---|---|---|---|---|
| Unemployment rate | 0.37 | -0.01 | 0.05 | 7.45 | 0.00 |
| Sectorial diversification | 0.01 | -0.01 | 0.04 | 0.51 | 0.30 |
| Sectorial composition | 0.08 | -0.01 | 0.05 | 1.97 | 0.02 |
| Share of low education | 0.68 | -0.01 | 0.05 | 13.76 | 0.00 |
| Gross domestic product | 0.41 | -0.01 | 0.05 | 8.23 | 0.00 |
| *1-tail test | | | | | |

An other important aspect for the estimation of the model is the presence of an high spatial correlation across regions that could influence the estimates. This correlation could be representative of a specific territorial development model. From the econometric point of view, this means considering a lagged spatial variable or a spatial error model, to be chosen using appropriate tests of spatial specification.

## 2. *Estimation*

The empirical research strategy was to estimate a baseline model explaining the territorial variability of the unemployment rate in year 2006 following eq. (2) without variables regarding size. In the model we controlled for spatial autocorrelation. Then, we inserted variables explaining agglomeration in the specification and verified their statistical effects as in eq.(3).

The conditioning variables include the effects of sectorial structure and its diversification, size, the human capital and development level. The model is proven to be statistically significant, and the variability explained is close to 60%.

The results shows that sectorial diversification reduces the unemployment rate while the sectorial composition is a factor of increase. This data is consistent with the empirical result of a negative correlation between the dynamics of the unemployment rate and of the aggregate demand.

All the spatial tests suggest the presence of a strong spatial dependence of errors in the model .

Tests are not able to discriminate between a spatial error and a spatial lag model (Anselin et al., 1996). At the end, we presented the results for the spatial lag specification, estimated by a ML estimator. In each estimated spatial lag model the residuals do not present spatial dependence.

Correcting for spatial dependence, the structure of the model does not change; it presents only a different sign in the coefficient related to the sectorial composition variable. Given the difference in the size of the economy in the regions it is plausible that national shocks do not capture well specific sectorial shocks.

The coefficient related to the level of education is positive: this means that the variable detects negative shocks specific for those regions. The specification of urban agglomerations was represented by different variables. The main results are the following:

1. the agglomerative effect due to the size of the population and the labour forces is positive and significant, (Tab. 6). Even if the working-age population is inserted in the equation, the sign does not change.
2. the effect due to a higher density of the population per square km, which thus regards the relative "thickness" of markets, is positive and significant.

The analysis evaluates the effects attributed to industry agglomeration, exploiting different variables here as well. The results are partially different from those obtained for urban agglomerations:

1. the use of variables such as number of employees and their logarithm leads to a positive coefficient. Such variables are, however, closely correlated cross sections of those regarding population, and thus detect only very approximately the effects of industrial agglomerations (Tab. 7).
2. if, instead, we simultaneously insert population density and business density, we obtain a positive coefficient for the former and a negative one for the latter. They are significant in

both cases. This could mean that when the effects of urban agglomeration are negative we observe positive business agglomerations. The result can be interpreted by claiming that while the first variable detects congestion diseconomies, the second one detects thick market economies.

The results regarding business agglomerations, even if somewhat conflicting, indicate that the presence of agglomeration economies has positive effects on the labour market.

## 3. Conclusions

The model proposed by Gan and Zhang (2006) shows how the presence of agglomeration externalities, linked to the presence of thick labour markets, captures the geographic variability of the unemployment rate (and its fluctuations). However, the authors do not explain if agglomeration depends on urbanisation, i.e. aggregations of people, or else depends on the presence of industrial clusters, i.e. firm's aggregations. This is because in the United States the two agglomerations tend to coincide, as large cities often grow alongside their industrial areas.

This does not occur in many European countries. In several European countries, for instance in Italy, many firms clusters (in some cases referred to as districts) spring up in areas adjacent to medium sized or small cities. The transposition of the results of the model is thus not automatic, and requires an adaptation of the spatial distribution of the population and firms.

The results clearly show that, unlike what was empirically found by Gan and Zhang (2006) for the United States and by Di Addario (2005), even if only to a slight degree, for Italy, urban agglomerations have negative effects on the unemployment rate of the area. The same results show how industrial agglomerations have positive effects on the labour market, confirming and extending the results of de Blasio e Di Addario (2005). The results are more interesting when we consider both agglomerations: the industrial clusters have a positive effect on the employment, while is still negative the effect of urban agglomeration. We can conclude that only an aggregation of firms empirically generates the market externalities often mentioned by the model.

This conclusion is not surprising: in Marshall's studies as well, labour market pooling was indicated as a source of business district externalities. The conclusion that such effects only occur among firms is less automatic. This can mean that an aggregation of firms is able to already take into account the presence of specific skills in the area, which in turn strengthen their competitive potential. An urban aggregation, instead, follows a different logic which does not necessarily link the requested skills to firms.

There are many policy implications that can be derived from our results. First of all, government should increase the circulation of labour market information in order to enhance the matching between job seekers and labour positions even in urban areas. Incentive for reducing the costs of search cannot obviously be limited to the case of contiguity between the supply and demand of skills, but also regards the acquisition of information and knowledge which often occurs through informal chains, less strong in urban centres. Improvements in the quality of the matching require policies able to disseminate information which can substitute those channels. It is important to reduce the costs of getting information in order to avoid the discouraging effect on job search activities.

The study also suggests how supporting the creation of business clusters, even if not in the vicinity of urban areas, can improve labour market conditions and increase matching efficiency. The result is not necessarily linked to the presence of industrial districts: from this point of view, less specialised areas with a larger sectorial diversification turn out to be, from our model, more capable of absorbing negative sectorial shocks and of reducing the average level of unemployment in the area.

*Table 3 Regression results of baseline model.*
*Estimation method: OLS*

| *Variables* | *Baseline model* |
|---|---|
| Sectorial diversification | -1.93<br>[0.85]* |
| Sectorial composition | 20.71<br>[6.72]** |
| Gross domestic product | -4.38<br>[1.31]** |
| Share of low education | 9.43<br>[4.55]* |
| Country effect | Yes |
| Constant | 48.39<br>[13.84]** |
| Observations | 105 |
| R-squared | 0.56 |
| Adj R-squared | 0.49 |
| Root MSE | 2.42 |

*Notes*: Standard errors in brackets.
* significant at 5%; ** significant at 1%.

*Table 4 Spatial autocorrelation test, results for baseline model.*

| **Test** | **Statistic** | **Df** | **p-value** |
|---|---|---|---|
| Spatial error: | | | |
| Moran's I | 5.476 | 1 | 0.000 |
| Lagrange multiplier | 9.319 | 1 | 0.002 |
| Robust Lagrange multiplier | 5.423 | 1 | 0.020 |
| | | | |
| Spatial lag | | | |
| Lagrange multiplier | 25.838 | 1 | 0.000 |
| Robust Lagrange multiplier | 21.942 | 1 | 0.000 |

*Table 5 Baseline model corrected for spatial dependence.*
*Estimation method: ML*

| *Variables* | *Spatial baseline model* |
|---|---|
| Sectorial diversification | -1.86<br>[0.66]** |
| Sectorial composition | 16.17<br>[5.26]** |
| Share of low education | 6.97<br>[3.55]* |
| Gross domestic product | -1.9<br>[1.09] |
| Constant | 20.13<br>[11.60] |
| Country effect | Yes |
| ρ (spatial lag coefficient) | 0.67<br>[0.10]** |
| log likelihood | -219.5 |
| Variance ratio | 0.62 |
| Squared corr. | 0.69 |
| Wald test of ρ = 0 | 41.78** |
| LR test of ρ = 0 | 26.9** |
| LM test of ρ = 0 | 25.8** |
| Observations | 105 |

*Notes*: Standard errors in brackets.
* significant at 5%; ** significant at 1%, °significant at 10%.

*Table 6 Urban agglomeration*
*Estimation method: ML*

| *Variables* | *model 1* | *model 2* | *model 3* |
|---|---|---|---|
| Sectorial diversification | -2.29 [0.68]** | -0.48 [0.50] | -0.77 [0.50] |
| Sectorial composition | 15.92 [5.17]** | 11.34 [3.88]** | 12.99 [3.95]** |
| Share of low education | 8.09 [3.54]* | 5.33 [2.60]* | 5.81 [2.66]* |
| Gross domestic product | -1.69 [1.07] | -7.36 [1.04]** | -7.23 [1.06]** |
| Ln population | 0.46 [0.24]° | - | - |
| Population density | - | 0.002 [0.00]** | - |
| Labour force density | - | - | 0.01 [0.00]** |
| Constant | 10.63 [12.35] | 75.38 [10.94]** | 73.96 [11.15]** |
| Country effect | Yes | Yes | Yes |
| | | | |
| ρ (spatial lag coefficient) | 0.67 [0.10]** | 0.38 [0.11]** | 0.38 [0.11]** |
| log likelihood | -217.6 | -183.13 | -185.37 |
| Variance ratio | 0.63 | 0.82 | 0.82 |
| Squared corr. | 0.7 | 0.84 | 0.83 |
| Wald test of ρ = 0 | 43.3** | 12.1** | 11.89** |
| LR test of ρ = 0 | 27.7** | 10.7** | 10.6** |
| LM test of ρ = 0 | 25.9** | 10.7** | 10.6** |
| Observations | 105 | 105 | 105 |

*Notes*: Standard errors in brackets.
* significant at 5%; ** significant at 1%, °significant at 10%.

*Table 7 Industrial agglomeration.*
*Estimation method: ML*

| *Variables* | *model 4* | *model 5* | *model 6* |
|---|---|---|---|
| Sectorial diversification | -0.31<br>[0.52] | -0.51<br>[0.49] | -2.27<br>[0.69]** |
| Sectorial composition | 11.76<br>[4.00]** | 8.93<br>[3.83]* | 16.16<br>[5.18]** |
| Share of low education | 4.32<br>[2.69] | 3.86<br>[2.56] | 7.96<br>[3.54]* |
| Gross domestic product | -7.64<br>[1.10]** | -7.99<br>[1.04]** | -1.95<br>[1.07] |
| Employment density | 0.004<br>[0.00]** | - | - |
| Manufacturing employment density | - | 0.05<br>[0.01]** | - |
| Ln employment | - | - | 0.43<br>[0.24] |
| Constant | 78.46<br>[11.57]** | 81.3<br>[10.98]** | 14.16<br>[11.86] |
| Country effect | Yes | Yes | Yes |
| ρ (spatial lag coefficient) | 0.39<br>[0.11]** | 0.46<br>[0.10]** | 0.67<br>[0.10]** |
| log likelihood | -186.52 | -181.71 | -217.94 |
| Variance ratio | 0.81 | 0.83 | 0.63 |
| Squared corr. | 0.82 | 0.84 | 0.7 |
| Wald test of ρ = 0 | 13.05** | 20.37** | 43.4** |
| LR test of ρ = 0 | 11.47** | 17.11** | 27.8** |
| LM test of ρ = 0 | 11.22** | 16.64** | 26.1** |
| Observations | 105 | 105 | 105 |

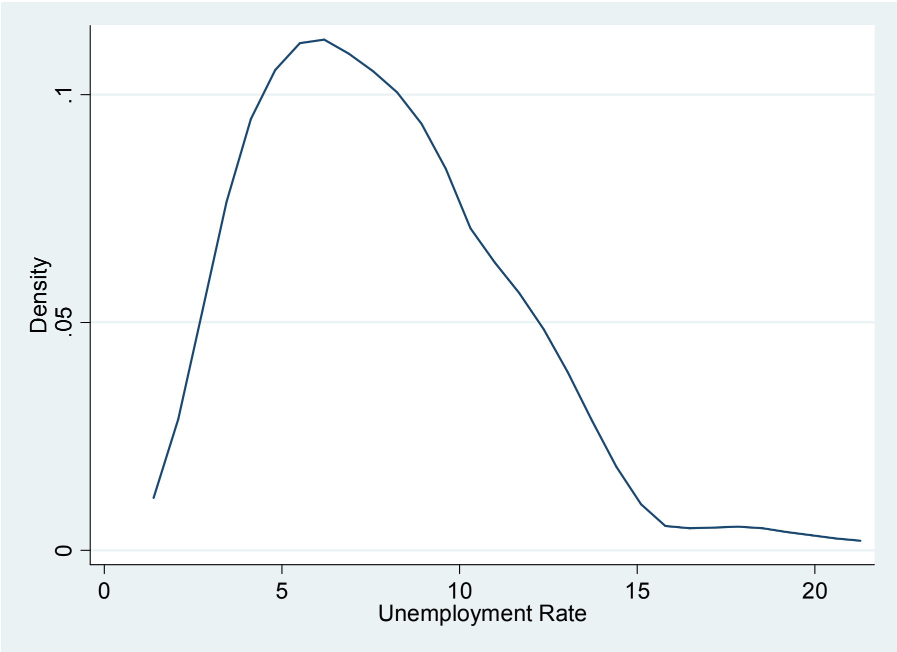
*Notes*: Standard errors in brackets.
* significant at 5%; ** significant at 1%, °significant at 10%.

*Table 8 Urban and Industrial agglomeration.*
*Estimation method: ML*

| *Variables* | *model 7* | *model 8* |
|---|---|---|
| Sectorial diversification | -0.43<br>[0.49] | -0.32<br>[0.47] |
| Sectorial composition | 9.71<br>[3.81]* | 5.56<br>[4.04] |
| Share of low education | 4.39<br>[2.55] | 6.12<br>[2.56]* |
| Gross domestic product | -8.0<br>[1.04]** | -8.65<br>[1.04]** |
| Agriculture employment share | - | -13.43<br>[5.31]* |
| Population density | 0.002<br>[0.00]° | 0.002<br>[0.00]* |
| Manufacturing employment density | -0.03<br>[0.01]* | -0.03<br>[0.01]* |
| Constant | 81.57<br>[10.91]** | 87.54<br>[10.85]** |
| Country effect | Yes | Yes |
| ρ (spatial lag coefficient) | 0.41 | 0.44 |
| | [0.10]** | [0.10]** |
| log likelihood | -176.92 | -176.92 |
| Variance ratio | 0.84 | 0.84 |
| Squared corr. | 0.85 | 0.85 |
| Wald test of ρ = 0 | 14.89** | 18.45** |
| LR test of ρ = 0 | 12.98** | 15.68** |
| LM test of ρ = 0 | 12.83** | 15.32** |
| Observations | 105 | 105 |

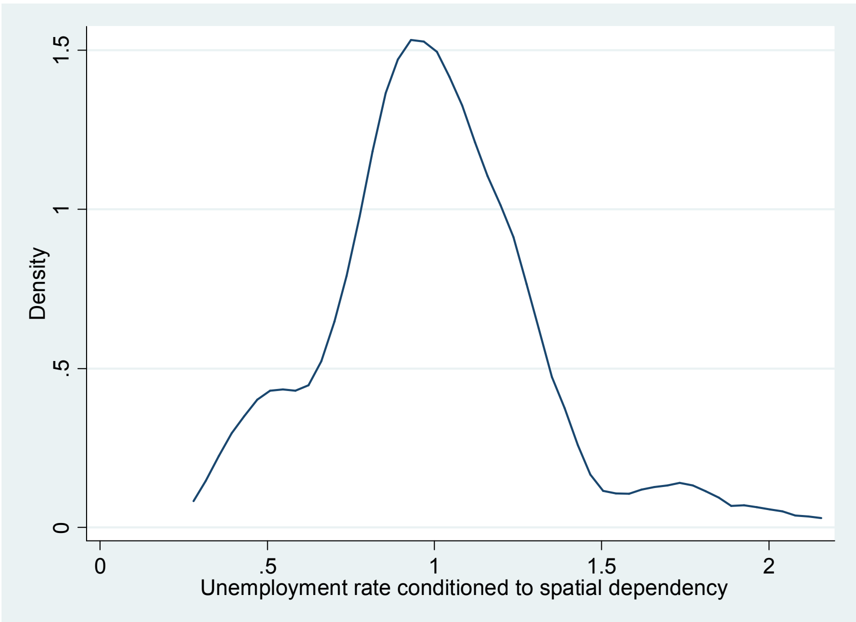
*Notes*: Standard errors in brackets.
* significant at 5%; ** significant at 1%, °significant at 10%.

*Figure 1 – Kernel density of unemployment rate with Epanechnikov function*




*Source*: Own elaboration on OECD.Stat, Labour Force Statistics (MEI)

*Figure 2 – Kernel density of unemployment rate conditioned to spatial dependency with Epanechnikov*




*Source*: Own elaboration on OECD.Stat, Labour Force Statistics (MEI)

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