44th European Congress of the European Regional Science Association.

Porto, 25-29 August 2004.

Knowledge, networks of cities and growth in regional urban systems: theory, measurement and policy implications

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Abstract: The objective of this paper is to measure the impact of different kinds of knowledge and external economies on the urban growth in an intraregional network of cities. The paper is divided in five sections. First section (theoretical framework) exposes the relation between the knowledge-based city, networks of cities, external economies and urban growth. Second section exposes a methodology for the measurement of knowledge in cities and the identification of knowledge-based networks of cities. Third section exposes a model to measure the effects of knowledge and external economies (static and dynamic) on the urban growth. Fourth section applies this model to a case study (Catalonia). Finally, conclusions and policy implications are exposed.

JEL: R11, R12, O3

Keywords: knowledge-based city, networks of cities, urban growth, external economies, spatial econometrics.

1. Theoretical framework

1.1. Knowledge-based economy, cities and networks of cities

Romer (1986) formalized the relation between knowledge and economic growth. The main characteristic of knowledge is that it is a non rival good, because the utilization of knowledge for an actor do not reduces the quantity available for another actor. This lack of rivalry implies the possibility of increasing returns in the production function. In the model of Romer, imperfect competition is needed in order to remunerate knowledge accumulation (Schumpeterian framework). However, knowledge accumulation can also occur as an accidental subproduct generated from the activity of the actors in the economy (Jones 1998). In this case, knowledge accumulation can arise from the existence of externalities. On the other hand, there is a spatial nexus between knowledge, externalities and growth. Knowledge is not disperse but is concentrated in urban units (cities, metropolitan areas). The concentration of actors in the same urban units also facilitated the generation of externalities, when a part of these externalities are knowledge spillovers.

Cities are not isolated systems but rather they are linked to other cities forming networks. A network of cities is a structure where the nodes are the cities, connected by links of different kind through which flows of socioeconomic nature are exchanged. These flows are supported on communication and telecommunication infrastructures. The main characteristics of the networks of cities are the possibility of hierarchical and non-hierarchical structures, competition-cooperation between the cities, and the generation of advantages related to the organization and exchanges between the cities. Links between cities can be specified using information and knowledge flows. This approach allows analyzing the processes of generation and diffusion of knowledge through the urban structure. Previous to the network paradigm, the *central place models* related the production of innovations to the rank of the city in the urban system (Webber 1972). In these models, the amount of cumulate knowledge was ordered in a hierarchical way because depended on the population of each city. Then, innovations and knowledge spread in a hierarchical way from major cities to minor cities. In the modern *network paradigm*, knowledge diffusion cannot only be carried out in a vertical way, but also among cities of the same rank and from cities of lower rank to cities of higher rank. Thus, the existence of stable relational channels between the cities can also generate knowledge spillovers (Pred 1977).

1.2. Networks of cities, external economies and economic growth

Marshall (1920) use the terms *internal* and *external economies* to explain that increasing returns in the production can originate in factors that are "internal" and "external" to the firm[1]. Internal economies are produced and appropriated inside the firm. External economies describe a situation where the firms have advantages coming from outside the firm. According to Meade (1952) and Scitovsky (1954), an external economy in the production is generated when the output (y_k) of a firm k depends not only of the factors of production used by the firm (l_k, c_k, ...), but also of the output ($y_{k'}$) and the factors ($l_{k'}$, $c_{k'}$, ...) used by others firms k' [2]:

$$y_k = F(l_k, c_k, ...; y_{k'}, l_{k'}, c_{k'} ...) \qquad \forall k' \neq k \qquad [1]$$

The existence of external economies allows increasing returns in an industry (sector) although their firms have perfect competition curves.

Urban economics uses the concept of "agglomeration economies" to describe the relation between internal/external economies and the cities. Weber (1929 p.124-168) introduces the generic concept of "factors of agglomeration" to refer to the elements that determine the localization of the economic activity related to the advantages that the firms obtain from be localized in a densely industrialized area. The base of the mechanism of agglomeration is that under the influence of transportation costs,

[1] ["We may divide the economies arising from an increase in the scale of production of many kind of goods, into two classes – firstly, those dependent on the general development of the industry; and, secondly, those dependent on the resources of the individual houses of business engaged in it, on their organization and the efficiency of their management. We may call the former *external economies* and the latter *internal economies*."] (Marshall 1920, p.221). Marshall's original definition do not refers that this industries were concentrated. Later on, Marshall declares his interest about concentration economies: ["…; but we now proceed to examine those very important external economies which can often be secured of the concentration of many small businesses of a similar character in particular localities: or, as is commonly said, by the localization of industry"] (Marshall 1920, p.221).

[2] Mishan (1971) add the requirement that the effect would be not foreseen (incidental). The equation corresponds to the "technological external economies" in the article of Scitovsky (1954, p. 145), and its adaptation to "pecuniary economies" is immediate.

manufacture firms trend to concentrate in a limited number of places. The objective is minimizing the transportation costs to the sources of raw materials and final markets. Ohlin (1933, p.203) identifies other advantages derived from concentration that are not necessarily related to differences in transportation costs. These advantages are called "concentration economies", and we can differentiate three categories: "economies of concentration of industry in general", "external economies of concentration of a particular industry" and "internal large-scale economies of a producing unity". Hoover (1937, p. 90-91) popularized Ohlin's taxonomy using the terms: *large-scale economies* within a firm (generated by the enlargement of the firm's scale of production at one point), *localization economies* (caused by the total growth of a industry in a place, that affects firms of this industry) and *urbanization economies* (generated by the enlargement of the total economic size in terms of population, income, output or wealth, that affects all the firms in this place). Hoover's taxonomy has been the most utilized in urban and regional economics, although additional factors have been incorporated, for example diversity as source of urbanization economies after Chinitz (1961) and Jacobs (1969)[3]. We can represent agglomeration economies in a generic way:

$$y_{k,i} = F(l_{k,i}, c_{k,i}, \ldots; y_{k',i'}, l_{k',i'}, c_{k',i'} \ldots \theta_j) \qquad \forall\, k' \neq k \qquad [2]$$

, k is the firm and i is the sector. If $i=i'$ intra-industry external economies are generated. If $i \neq i'$ inter-industry external economies are generated. The component θ_j incorporates the external economies generated by other urban factors.

Following Hoover (1937), agglomeration economies show two characteristics: they are *temporally* and *spatially static*. The former is studied by Glaeser et al. (1992) introducing the distinction between static and dynamic external economies[4]. The latter

[3] Camagni (1992, p.46-57) provides an actualized and exhaustive compilation of these factors.
[4] Theories of (temporally) dynamic externalities explain simultaneously how the cities are born and grow. Theories of (temporally) static externalities, represented by the traditional conception of localization and urbanization economies, explain the formation of cities and their specialization but not their growth. From this approach we can differentiate between localization *economies* (temporally static) and *MAR externalities* (temporally dynamic), and between *urbanization economies* (temporally static) and *Jacobs economies* (temporally dynamic) (Glaeser et al. 1992, p.1128).

(spatial dynamics) are present when we approach the city as a node in a system of cities, and not as an isolated entity[5].

The generation of external economies related to the interaction between cities, and therefore spatially dynamic, is studied by the theories of the *network of cities* (Pred 1977; Dematteis 1989; Camagni and Salone 1993). The central theory of this paradigm is that there are economies/diseconomies associated with the existence of networks of cities. These economies depend on the characteristics of the nodes and the interaction. Network economies can be generated from the supply side (production) or from the demand side. They are a source of increasing returns and competitive advantages, and contribute to the growth of the urban economies. We can incorporate an additional term to the previous equations:

$$y_{k,i,j} = F(\underbrace{l_{k,i,j}, c_{k,i,j}, \ldots}_{\text{Internal economies}}; \underbrace{y_{k',i',j}, l_{k',i'j}, c_{k',i'j} \ldots, \theta_j}_{\text{External agglomeration economies}}; \underbrace{y_{i',j'}, l_{i'j'}, c_{,i'j'} \ldots, \theta_{j'}}_{\text{External network eonomies}}) \quad \forall k' \neq k \;;\; j' \neq j \qquad [3]$$

, k is the firm, i is the industry and j the localization (city) [6]. Therefore, we can offer an additional element to explain the process of growth and development of the cities. The output of the firms is affected not only by internal factors but also by external advantages located in the same or different cities. Stable network relations among cities provide and additional source of external economies that affects the competitive advantages of the firms and generates economic growth[7,8].

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[5] Traditional regional and urban economics synthesize this approach in the central place models. The main feature of these models is to explain the organization of the urban systems forming nested hierarchies of centres. In their early versions (Christaller 1933; Lösch 1944), the relation with agglomeration economies was based on the internal scale economies generated by firms located in the main cities of the system when market size increases. Recent elaborations (Fujita, Krugman and Mori 1999) include localization economies and congestion diseconomies in hierarchical urban systems.

[6] Suffix *k'* is omitted from the third term of the equation. Thus, we can capture the aggregate effect of a generic urban unit on the unit of reference, and not the individual effect of a firm located in another different urban unit.

[7] Spatially dynamic economies are not a new phenomenon in the economic literature. At the same time that Ohlin and Hoover study concentration economies, Robinson (1931/1958 p.124-127) divide external economies in mobile and immobile. *Immobile economies* belong together with Hoover's localization economies. *Mobile external economies* are generated among specialized places (e.g. cotton industry in Manchester and Liverpool at the end of the XIX century). They do not depend on the size of a particular city, but on the size of the industry as whole, in a set of linked places. In fact, we can define these mobile economies as the spatially dynamic version of localization economies, where concentration in a single urban unit is not necessary. Thus, firms located in several cities can have the same advantages that if they were concentrated. Notice that although the mobile economies were known by Hoover (1937, p.90 note 4), regional and urban economics preferred to study concentration economies (spatially static).

2. Measurement of knowledge in cities and identification of knowledge-based networks of cities

2.1. Measurement of knowledge in cities

How can we measure the amount of knowledge in cities? The OECD provides some indicators that are applied to a country-level. Several of these indicators are based on adaptations of the activities and skills classifications (ISIC, ISCO) or the products classification (HS, through a conversion in ISIC). Trullén, Lladós and Boix (2002) propose to apply the OECD indicators to urban units and elaborate a municipal indicator based on the technology and knowledge classification of activities (OECD 2001) using employment data. According to the OECD (2001, p.140, 156 and 189) manufactures can be aggregated in four levels of technological intensity (high, medium-high, medium-low and low) and services in two levels of knowledge (knowledge intensive and knowledge non intensive)[9]. We include in a residual sector the activities not classified by the OECD (primary activities; extractives; energy and water; and construction). Although this classification needs three digits information, it can be adapted to two digits with a small loss of precision[10]. Table 1 provides the two digits adaptation of the OECD technology and knowledge classification, and the differences with the original three digits classification. Whether this indicator is a partial approximation to the city knowledge intensity, it has the advantage that employment data by industry use to be available at a municipal level and it uses to allow the elaboration of temporal series. Time series prove to be important to differentiate cyclical response of the different types of knowledge (Trullén, Lladós and Boix 2002).

We apply this two digits classification to Catalonia and its municipalities. Results show the employment level of each sector at 1991 and 2003 (figure 1). Regarding the year 2003, High-technology manufactures contains 14,970 employees; Medium-high

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[8] Little research has been carried out on the concrete mechanisms of generation of network externalities. We can identify some ways of generation of advantages: size effects, reduction of transaction costs, organizational advantages etc. In this paper we will centre on a concrete mechanism that is knowledge.
[9] Following Eurostat (2002), knowledge-intensive services would be subdivided in two intensities.
[10] "Pharmaceuticals" and "Aircraft and spacecraft", originally in the High-technology manufactures sector can not be disaggregated from "Chemicals" and "Transport Equipment", and will be included in Medium-high technology manufactures.

technology manufactures 177,300 employees; Medium-low technology manufactures 110,774 employees; Low-technology manufactures 248,042 employees; Knowledge-intensive services 628,891 employees; Knowledge-non intensive services 974,287 employees; and the residual sector (Other non classified activities) 240,580. Aggregating the data in only three sectors: high knowledge, low knowledge and residual sector, we obtain that High-knowledge activities contain the 34% of the employment, Low-knowledge activities contain the 55.62%, and the residual sector contains the 10.04%. Regarding the variation of the wage earning employment, High-technology manufactures increase in 8,148 employees (growth rate 119%), Medium-high technology manufactures loss 6,746 employees (-4%); Medium-low technology manufactures loss 51,916 employees (-32%); Low-technology manufactures loss 24,844 employees (-9%); Knowledge-intensive services increase 349,820 employees (125%); Knowledge-non intensive services increase 266,055 (38%), and the residual sector increases 52,714 employees (28%). Total employment increases 593,243 employees (33%). Whether low knowledge activities continue to be the dominant part of the structure of the employment, these data suggest that there are two simultaneous processes: first, a change from the manufacture to the services; second, a change towards more knowledge intensive activities.

Regarding the territorial distribution, the principal amount of high and medium-technology activities (manufactures and services) is concentrated in the central part of the metropolitan region of Barcelona and in other few cities like Tarragona, Reus, Girona and Lleida. Low and medium-low technology and knowledge activities are distributed along the metropolitan region of Barcelona, in other minor metropolitan areas of Catalonia (Girona, Lleida, Manresa and Tarragona-Reus) and in the corridors connecting these areas.

2.2. Identification of knowledge-based networks of cities

So far, researches on the identification of networks of cities have been few and heterogeneous. This heterogeneity arises from the different objectives of the research and data availability. It makes very difficult to compare the results of the different investigations.

We distinguish to kinds of methodologies. *Indirect methodologies* try to identify networks of cities using dynamized stock data or contrasting the differences with the Christallerian model. Examples of these methodologies are Dematteis and Emanuel (1989), and Camagni et al. (1994). *Direct methodologies* are based on the direct use of flows: there is a network link between two urban units A and B when there is a significant flow (cardinal or ordinal) between them. This methodology assumes a systemic approach where the issue is not divergence from Christallerian patterns. Examples of these methodologies are Pred (1977), Trullén and Boix (2001) and Boix (2002).

We use the municipality (city or town) as the spatial unit of analysis. This is not an ideal unit of analysis, but the use of other units like labour markets or metropolitan (micropolitan) areas imply aggregation and tend to change with the time[11]. On the other hand, the use of the municipality has some advantages: it is a disaggregated nodal urban unit and it has administrative autonomy. Catalonia contains 944 municipalities. Around 80% of the population live in units above 10,000 inhabitants (10% of the municipalities). The largest city is Barcelona, with 1.5 millions inhabitants. The distribution of the activity follows similar rules. Barcelona contains 30% of the jobs. The more important cities are distributed in the nucleus of the Metropolitan Region of Barcelona surrounding the old industrial subcentres or along motorway corridors.

Since no other data flows are available, we use commuting data (house to work) to identify the structure of the network. These data are linked to social relations and infrastructural endowment. Previous researches showed the capacity of this kind of flows to reveal the urban structure (Boix 2002)[12]. In 1991, there were 798,000 inter-municipality commuters (in 30,000 pairs of connexions A→B). In 2001, there were 1,285,000 inter-municipality commuters (in 42,000 pairs of connexions). However, a great number of these flows were of low volume. This derives from the small size of many municipalities. These low amount flows tend to be scarcely significant for the detection of the urban structure. For example, if we apply a filter of minimum 50

[11] The use of local labour markets can offers an additional perspective since they provide a different approach to the concept of urban unit of analysis. The metropolitan unit is also an interesting option when the research is carried out using an interregional approach.

[12] In a regional context, commuting flows are strongly correlated whit telephonic and retail flows. For a meticulous study of the productive relations, additional types of flows (like interfirm transactions) would be preferable.

commuters it remains only 1,748 pairs of connexions that embrace 655,661 commuters in 1991, and 3,159 pairs of connexions that embrace 1,070,000 commuters in 2001. This means that 82% of commuters move between the 6% and 7.5% of the intermunicipal relationships.

In order to capture the most relevant network relationships, we propose the *Flow Specialization Coefficient (FSC)*. This coefficient is a translation to a flow context of the location coefficient:

$$LC_{i,j}^{s} = \frac{F_{i,j}^{s}}{F^{s}} \Big/ \frac{F_i}{F} \qquad [4]$$

, where F = external commuting flow; s = sector; i = city of origin; j = city of destination.

A FSC coefficient above 1 indicates relative specialization in the structure of fluxes[13]. Thus, the FSC imposes a double restriction: the emitting city would have a relative specialization in this sector related to its labour force, and the attractor city would have a relative specialization in the sector in order to originate a differential of attraction. We applied the FSC to the knowledge aggregation of the industries (seven aggregates) using the data of the censuses of 1991. We identified these networks in a detailed way for each subsector inside each knowledge macro-sector. Then, we overlap these networks in order to form the networks for the seven aggregates. It is also possible to identify the networks directly using the aggregate data for the seven sectors. The advantage of using more disaggregate sectors is that in the posterior aggregation we can obtain the scores of the number of links inside each macro-sector.

The aggregated network (figure 2) contains the principal network relationships in the Catalonian system of cities. The city of Barcelona is the principal centre of the network, with a large amount of short and long distance flows. Removing Barcelona, we observe a meshed structure in the centre of the metropolitan region of Barcelona and a polycentric network around Tarragona-Reus-Valls. Other places show star-shaped

[13] Researchers use to filter for coefficients larger than one. Thus, we apply the filter above 1.25. Additionally, we impose two restrictions in order to remove non significant or stochastic behaviours in the smaller municipalities: flows above 10 commuters and that the flux account for minimum 1% of the total jobs in the city.

structures that are typical of the central place models (the networks of Girona, Lleida and Vilafranca del Penedès). The networks of Igualada, Manresa and Vic combines polarized structures with a trend to expand along the motorways towards the centre of the metropolitan region of Barcelona.

Isolating high and low knowledge networks (figure 3), two different patterns appear. A large amount of High-knowledge networks arise from the link with Barcelona (the city with higher levels of knowledge in the network). Removing Barcelona, we observe that the other high-knowledge network relationships are concentrated in the centre of the metropolitan region of Barcelona, in stars around Lleida, Girona and Manresa, and in a polycentric network around Tarragona-Reus-Valls. These networks have weak or inexistent connexions between them. Low-knowledge networks include a larger number of municipalities. Barcelona is the most important centre, but removing Barcelona, the network continues to maintain the structure. This network shows a less hierarchical pattern, with a meshed-polycentric centre in the core of the metropolitan region of Barcelona, stars around Lleida, Girona-Figueres, Vilafranca del Penedès and Igualada, a polycentric structure in Tarragona-Reus-Valls and some mixed pole-corridor structures around Manresa and Vic. These results suggest that the diffusion of high knowledge along the network of cities is concentrated inside the metropolitan region of Barcelona and the principal subcenters of the network. Barcelona plays a key role connecting with other more isolated parts of the network. On the contrary, the low knowledge network is denser and less hierarchical. This leads to the idea that while high-knowledge networks are decisive for the diffusion of new knowledge, low-knowledge networks can play a very important role generating network externalities to the low-knowledge industries.

3. A model to measure the effects of knowledge and external economies on the urban growth

This section exposes a model to measure the effects of knowledge and external economies (static and dynamic) on the urban growth. Two main approaches arise when knowledge or innovation are the objectives of the research (Autant-Bernard and

Massard 1999)[14]. The first one is the knowledge/innovation production function. The theoretical framework is based on Griliches (1979) and Grossman and Helpman (1991). Empirical applications use three main proxies for these variables: patents, expenditure or employment of personnel on R&D, and innovations introduced in market. Jaffe (1989), Jaffe, Trajtemberg and Henderson (1993) and Almeida and Kogut (1997) use patent citations as a proxy of knowledge. Kelly and Hageman (1999) and Paci and Usai (1999) use patent citations as a proxy for innovation. Acs, Audrestch and Feldman (1991), Feldman (1994), Feldman and Florida (1994), Audrestch and Feldman (1996) and Anselin, Varga and Acs (1997 and 2000) use innovations introduced in the market as a proxy for innovation. Multi-indicator measures are implemented in Zucker, Darby and Amstrong (1994) which use for each firm the number of products in development, the number of products in the market and the employment growth. Roper (2001) uses indicators of product innovation, process innovation, innovation intensity and innovation success as proxies for innovation.

The second approach is based on the effects of knowledge and innovation on the efficiency/productivity or on the economic growth. The theoretical framework is based on the economic growth theory and the models of endogenous growth (Solow 1957, Arrow 1962, Lucas 1988, Romer 1986 and 1990, and Arthur 1996). Empirical applications use production, productivity or employment growth as dependent variables, and knowledge or innovations are modelled inside the production function. The most influent researches are Glaeser, Kallal, Scheikman and Shleifer (1992) and Henderson, Kunkoro and Turner (1995). Other interesting contributions centred in knowledge and externalities are in Deidda, Paci and Usai (2002) and De Lucio, Herce and Goicolea (2002). A critical vision about the limitations of these approaches is provided by Breschi and Lissoni (2001).

Other issues appear in the empirical implementation of the latter both approaches. First, since initial productivity/efficiency measurements were temporally static, the temporal dimension typical of the growth models was pointed out after Glaeser et al. (1992) and Henderson et al. (1995). However, these models were spatially static. The rise of the

[14] Davies (1989) provides a review of the theoretical approaches to the innovation or knowledge production function (Schumpeter, Arrow, Demsetz, Scherer, Kamien and Scwhartz, Dasgupta and Stiglitz), measurement, diffusion, and efficiency/productivity related to market structure.

spatial econometrics (Anselin, 1988) and the development of specific software (SpaceStat) facilitated the introduction of the space, mainly in the knowledge/innovation production function approach, also called “spillover approach”. Second, the unit of analysis changes depending of the availability of information: regions, metropolitan areas, labour markets, cities/municipalities and firm information. Latter is preferred because allows avoiding aggregation bias, but sometimes it is not available or presents problems related to censure, truncation or unknown sample selection. When no firm information is available, the use of urban units (cities, metropolitan areas) or labour markets are preferred. Finally, the availability of data affects the chice of the dependent variable (production/productivity or employment) and the number of effects tested.

3.1. Models to measure external economies with limited information in a temporally dynamic and spatially static framework

3.1.1. Glaeser, Kallal, Scheikman and Shleifer (1992)

Glaeser et al. (1992) derive a function of growth starting from a function of labour demand without capital data. They suppose a firm in some industry and in a location with a production function dependent of a technology $A_t f(l_t)$ [5], where A represents changes in the level of technology and prices, l_t is the labour input and t is the time period[15]. Each firm of each industry takes as given the technology, the prices and the wages (w_t), and maximizes $\Phi = A_t f(l_t) - w_t l_t$ [6]. This equals the marginal product of labour with its price, which is the wage: $A_t f'(l_t) = w_t$ [7]. The equation is expressed in growth rates and linearized taking logarithms:

$$\log\left(\frac{A_{t+1}}{A_t}\right) = \log\left(\frac{W_{t+1}}{W_t}\right) - \log\left(f'\left(\frac{l_{t+1}}{l_t}\right)\right) \qquad [8]$$

Under the hypothesis that the level of technology in a city-industry is the product of the local and national components: $A = A_{local} \cdot A_{national}$ [9], the changes in the technology and the prices depend on a local and a national component. The growth rate of the local

[15] It allows for technological and pecuniary externalities, but only these derived from the labour.

technology is assumed to be exogenous to the firm and dependent on a vector of external economies *g*. Combining all the terms and assuming a functional form $f(l) = l^{(1-\alpha)}$, where $0 < \alpha < 1$, we obtain:

$$\alpha \log\left(\frac{l_{t+1}}{l_t}\right) = -\log\left(\frac{w_{t+1}}{w_t}\right) + \log\left(\frac{A_{nacional,t+1}}{A_{nacional,t}}\right) + g(\cdot) + u_{t+1} \qquad [10]$$

This equation can be estimated in the usual form: $y = X\beta + u$ [11].

3.1.2. Henderson, Kunkoro and Turner (1995)

To test for temporally dynamic externalities, Henderson et al. (1995) model city employment in each industry as a function of historical and current conditions in cities. The model assumes that the output of an industry *j* in a city *i* at the time *t* is $\Phi = A_{it} f(N_{it};...)$ [12], when *N* is the employment and *A* the level of technology. The equilibrium employment level for an industry *j* in a city *i* at the time *t* equals the marginal product of the input: $W_{it} = A_{it}(\cdot) f'(N_{it};...) P_{it}(\cdot)$ [13], where *W* is the nominal wage rate, *P* is the price of output given a downward sloping inverse demand function $P_{it}(\cdot) = P(N_{it}; MC_{it})$ [14], and *MC* are the regional characteristics. Again, the hypothesis is that A_{it} is a function of the externalities in the base year. Substituting *A(·)* and *P(·)* in the equation of equilibrium (equation 13), inverting and assuming that the changes in the technology depends on initial conditions, we obtain the reduced-form equation: $N_{it} = N(N_{i0}, W_{i0}, MC_{i0}, g_{i0})$ [15]. Assuming a log-log form and changing N_{i0} to the left-hand side, the formulation will be similar to Glaeser et al. (1992).

3.1.3. De Lucio, Herce and Goicolea

De Lucio et al. (2002) introduce a firm Cobb-Douglas function and endogenously derive the index to measure the knowledge externalities: $Y_{ijt} = A_{ijt} L_{ijt}^{\alpha} K_{ijt}^{\beta}$ [16], where *Y* is the production, *L* is the labour, *K* the capital, *A* the technology, *i* is the industry, *j* is the territory, *t* represents the time and *α*, *β* are the labour and capital coefficients, assumed to be constant[16]. The maximization and linearization of the production function produces: $\ln(Y_{ijt}) = \ln(A_{ijt}) + \alpha \ln(L_{ijt}) + \beta[\ln(w_{ijt}) + \ln(L_{ijt}) + \ln(\beta) - \ln(\alpha) - \ln(r_t)]$ [17]. In this model, factor prices are endogenous. The model is expressed in growth rates. Like Glaeser et al. (1992), the growth rate of the technology is assumed to depend on a local and a global component. The global component A_{global} captures exogenous changes in the technology. The local component A_{local} is endogeneized, and like Grossman and Helpman (1991) and Martin and Ottaviano (1996), the model considers that the distribution of new innovations is a linear and increasing function proportional to the past number of local innovations in the industry. The local component of labour productivity growth depends on the generation and diffusion of innovations: $dA_{ijt}/dt = A^{*}_{ijt}(g_0)$ [18], where g is a vector of explanatory variables including external economies. Resolving the differential equation: $A^{local}_{jit} = A^{local}_{jit-1} e^{g(\cdot)t}$ [19], and integrating all terms we obtains: $\ln(Y_{ijt}/Y_{ij0}) = \beta_0 + \beta_1 \ln(L_{ijt}/L_{ij0}) + \beta_2 \ln(W_{ijt}/W_{ij0}) + \beta_3 \ln(\phi_{ijt}/\phi_{ij0}) + g(\cdot)$ [20], where ϕ is the productivity. If not enough information is available, we can assume a functional form with only an input $\Phi = A_{ijt} L^{1-\alpha}_{ijt}$, and the model will be similar to Glaeser at al. (1992) and Henderson et al. (1995).

3.2. Modifications to the GKSS, HKT and dLHG models

Glaeser et al. (1992), Henderson et al. (1995) and De Lucio et al. (2002) arrive from different ways to a similar specification. This specification allows estimate a production function with one (or several) inputs in a temporally dynamic framework. We can add two transformations to the final equation. First, since our ambit of analysis is intraregional, the labour market will be integrated. Thus, the growth of the nominal wage in each industry will be similar between different urban units[17]. Furthermore, if there were local differences for a sector, Glaeser et al. (1992) and Henderson et al. (1995) suggest that they can arise from the incorporation of external economies like a premium on the wage: $W_{ijt}/W_{ij0} = (1+\theta)(w_{ijt}/w_{ij0})$ [21], where W is the nominal wage, w is the real wage and θ is the premium due to the externalities. Under this assumption,

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[16] $K_{ijt} r_t / L_{ijt} w_{ijt} = \beta / \alpha$.

[17] This hypothesis is also suggested in Glaeser et al. (1992, p. 1134). Indeed, this is confirmed when the authors use the wage growth as the dependent variable in the estimations. In our empirical application on Catalonia the wage growth is fixed in a regional negotiation.

the wage can be removed when separate industry estimations or intra-groups estimators are carried out (demeaned equation)[18]. The same will be true for the interest rate. Then, the term θ will be incorporated in the vector of external effects *g*.

Second, the above-mentioned formulations do not specifically include internal economies (scale, scope, transaction costs, Schumpeterian innovation). In the exogenous derivation of Glaeser et al. (1992) and Henderson et al. (1995) internal economies confronts with the assumption of exogeneity of technology and prices. Glaeser et al. (1992, p.1142) avoid partially this problem including the inverse of a firm size vector like a competition index. Combes (2000a, p.334) argues that in the endogenous growth model spirit, large plants will be penalized if internal returns are decreasing. An alternative explanation arises from the importance and dynamism of the small firms in the processes of growth as is suggested by Becattini (1990).

Thus, the demeaned GKSS model takes the form:

$$[y-\overline{y}]=[f(\cdot)-\overline{f(\cdot)}]+[g(\cdot)-\overline{g(\cdot)}]+u \qquad [22]$$

or taking $y^*=[y-\overline{y}]$, $f^*=[f(\cdot)-\overline{f(\cdot)}]$ and $g^*=[g(\cdot)-\overline{g(\cdot)}]$

$$y^*=f(\cdot)^*+g(\cdot)^*+u \qquad [23]$$

, where $y=\alpha\log\left(\frac{l_{t+1}}{l_t}\right)$, *f(·)* is a vector of characteristic of the firm, and *g(·)* is a vector of external economies, including knowledge and not knowledge externalities (dynamic and static in the GKSS nomenclature). This demeaned equation can be estimated in the usual form: $y=X\beta+u$, excluding the constant term[19].

3.3. Extension to a spatially dynamic framework

The assumption that technology depends of some local and some national factors is too general. It neglects the mechanisms of generation, transmission, adoption and feedback of externalities and knowledge through the urban system. In the theoretical introduction,

[18] Other researches like Combes (2000a) acts in a similar way when do not includes the wages in the estimations.
[19] See Johnston and Dinardo (1997).

we extended the traditional framework of the *central place* models (Christaller 1933; Lösch 1940) towards the *network of cities* (Pred 1977; Camagni and Salone 1993). We can consider that the technology depends of three components: local, network and national/international: $A = A_{local} \cdot A_{network} \cdot A_{national/international}$. The network component includes knowledge and other externalities generated in the other cities of the network or transmitted through the network of cities. This can be exogenously incorporated like Glaeser et al. (1992) and Henderson et al. (1995), or endogenously derivated using a model of distribution of new innovations like De Lucio et al. (2002). Spatial econometrics (Anselin 1988) provides an easy way to deal with the specification of this network extension. Network relationships can be incorporated using a matrix of spatial contacts *W*. This matrix is not the matrix of geographical proximity used in most of the spatial econometric specification but rather corresponds to the knowledge-based networks identified in section 2.2 and allows for short and long physical distance interactions. Following the previous models, network externalities should arise from the initial conditions located in the other nodes of the network. Thus, it will take the form of a *cross regressive spatial model*:

$$y = X\beta + WX\gamma + u \qquad [24]$$

Three additional options can be taken account. First, following the usual specifications of the spatial econometric applications, knowledge externalities can arise from the simultaneous growth of the sector in the other cities of the network (*spatial lag model*)[20]: $y = \rho Wy + X\beta + u$ [25]. Second, these two specifications can be combined in a *regressive-regressive spatial model*, including network lags of the dependent and explanatory variables: $y = \rho Wy + X\beta + WX\gamma + u$ [26]. Finally, we can consider that knowledge externalities are transmitted through stochastic shocks along the network of cities, and the network effect is incorporated in the error term (*spatial error model*):

$$\begin{aligned} y &= X\beta + u \\ u &= \lambda Wu + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I) \end{aligned} \qquad [27]$$

[20] In the growth models, this specification suffers of causality problems, as is pointed out in Upton and Fingleton (1985).

All these models can be combined to produce a family of spatial models (Anselin 1988) or extended to more complex specifications. These models allow to simultaneously estimating concentration (agglomeration) and network externalities. Otherwise, it is possible to obtain that network effects are not significant.

4. Econometric measurement

This section is addressed to the application of the time and space dynamic growth model exposed in section 3 to a case of study: Catalonia.

4.1. Database

The data used in the estimations comes from several databases: firms, salary earner employment and self-employment (Labour Department, INSS and Gencat); export firms (Acicsa / Copca); population and education levels by age (Censuses / Idescat); average income by municipality (Department of Economy / Idescat); travel time and distance between municipalities (Visual Map road planner); primary, secondary and university education centres (Department of Education, Gencat), health centres (hospitals and other health centres, source: Health Department / Gencat); ports and airports (source: several departments of the Gencat); and commuting (travel to work) by municipality and industry (Censuses / Idescat). Employment, firms and commuting data are available by industry and municipality. Population, average income, education and infrastructure data are used at municipal level. The data were aggregated in seven macro-sectors using the OECD knowledge-based industry classification explained in section 2.1.

The first issue that may be addressed is the *definition of the relevant unit of analysis* for the econometric estimations. Although Catalonia is composed by 944 municipalities, a large amount of these ones are micro-municipalities. Per example, at 1991 only 84 municipalities were above 10,000 habitants, other 61 were above 5,000 habitants, and 543 municipalities were smaller than 1,000 habitants. This will lead to a problem associated with the number of zeros by industry and other related to outliers. However, Sforzi (1999, p.19) relates the problem of the unit of analysis to the definition of an intermediate unit between the productive process and the economic system as whole.

This unit must complete two requisites: it must be isolable for the study and it must be a tool for interpreting the economic reality. Thus, we decide to define like relevant economic units these municipalities that have employment in six of the seven macro-sectors in the analysis. This is debatable, but allows to identify the relevant economic units. This leads to use a sample of 267 municipalities as relevant urban units. These units includes the 96% of the wage earner employment at the years 1991 and 2003 (1,734,186 and 2,277,842 employees) and explains the 96.6% of the total variation in wage earner employment (543,656 employees on 563,003)[21]. Additionally, we will test for a possible selection bias.

4.2. Variables

Following the modified model exposed in the section 3, we will estimate a labour demand equation without factor prices (because they are incorporated in the vector of externalities) as a growth model with network effects. According to this model, the *dependent variable* is the logarithm of the growth rate of the wage earner employment between 1991 and 2003. The *explanatory variables* were divided in three sets: firm characteristics, concentration economies and network economies.

4.2.1. Firm characteristics

It includes firm size if the industry growth is related to the scale of the firm (Schumpeterian approach) or to the existence of small firms in a dynamic environment (Marshall – Becattini approach). Glaeser et al. (1992) and Combes (2000a) argue that in presence of decreasing returns (competitive market), this variable will be negative.

4.2.2. Concentration (agglomeration economies)

It includes most of the factors pointed out in the literature about external economies: Marshall (1920), Weber (1929), Ohlin (1993), Hoover (1937), Chinitz (1961), Jacobs (1969), Porter (1990) and Camagni (1992). This includes specialization effects (location coefficient), international competition (number of export firms), diversity (inverse of the

[21] A less restrictive option could be the aggregation of the other municipalities in supra-municipal units. However, a considerable amount of zeros continue to remain.

Hischmann-Herfindahl index), population and income (market size and profundity), human capital (average education), transport costs (road infrastructures) and other infrastructures related to transport, health and education. For specific inter-industry knowledge externalities we include the percentage of the knowledge sectors at the initial year[22]. Finally, the growth rate of self-employment is included in order to correct its effect on the salaried employment. Following the theoretical model, all variables were expressed in logarithms[23].

4.2.3. Network economies

Two strategies are used to control network effects. The first one is the inclusion of some connectivity indexes (Capello 2000; Trullén and Boix 2001). These indexes were constructed using the number of network connexions as an indegree or outdegree indicator. Following Camagni and Salone (1993) and Boix (2004), we differentiate between synergy/specialization networks (intra-industry networks) and complementarity networks (inter-industry networks). Thus, we obtain four index: indegree synergy, indegree complementarity, outdegree synergy, outdegree complementarity. The indegree index take account the subcenter role played by some cities.

The second strategy is the estimation of the spatial model with exogenous lagged variables (section 3.3, eq.18), testing for additional simultaneous lag or error effects. For intra-industry network effects we include the specialization index and the number of export firms multiplied by the specialized (synergy) network of each sector (*WS*). For inter-industry network effects (complementarity) we include the index of diversity, population, income, other infrastructures, and the percentage of the other knowledge sectors, multiplied by the complementarity network for each sector, which in this case coincides with the total network of each municipality (*WT*). The network matrices were row-standardized. Again, according to the theoretical model, all variables were expressed in logarithms.

[22] The percentage of each sector is excluded because it is included in the specialization index. Include it again will cause strong collinearity.

[23] Note that the usual variable of initial employment level is not included. Combes (2000b) argues that the inclusion of this variable leads endogeneity and changes the interpretation of the location coefficient. Furthermore, in some sectors it is highly correlated with the population.

4.3. Models and econometric strategy

Three main models arise from the latter variables: a linear non spatial model; a linear non spatial model with degree indexes for network effects, and a cross-regressive spatial model. Since the dependent and explanatory variables are expressed in logarithms and the network matrices row-standardized, the coefficients can be interpreted like direct elasticities.

Linear non spatial model:

$$\begin{aligned} Y = {} & \beta_1 DIM_{ij0} + \beta_2 SP_{ij0} + \beta_3 EXP_{ij0} + \beta_4 DIV_{ij0} + \beta_5 P_{j0} + \beta_6 INC_{j0} + \\ & + \beta_7 AEDU_{j0} + \beta_8 Inf_{j0} + \beta_9 OInf_{j0} + \beta_{10} LHT_{j0} + \beta_{11} LMHT_{j0} + \\ & + \beta_{12} LMLT_{j0} + \beta_{13} LLT_{j0} + \beta_{14} LKS_{j0} + \beta_{15} LNKS_{j0} + \beta_{16} LO_{j0} + e \end{aligned} \quad [28]$$

Linear non spatial model with degree index for network effects:

$$\begin{aligned} Y_{ij0} = {} & \beta_1 DIM_{ij0} + \beta_2 SP_{ij0} + \beta_3 EXP_{ij0} + \beta_4 DIV_{ij0} + \beta_5 P_{j0} + \beta_6 INC_{j0} + \\ & + \beta_7 AEDU_{j0} + \beta_8 Inf_{j0} + \beta_9 OInf_{j0} + \beta_{10} LHT_{j0} + \beta_{11} LMHT_{j0} + \\ & + \beta_{12} LMLT_{j0} + \beta_{13} LLT_{j0} + \beta_{14} LKS_{j0} + \beta_{15} LNKS_{j0} + \beta_{16} LO_{j0} + \\ & + \beta_{17} IS_{ij0} + \beta_{18} IC_{ij0} + \beta_{19} OS_{ij0} + \beta_{20} OC_{ij0} + e \end{aligned} \quad [29]$$

Cross regressive spatial model:

$$\begin{aligned} Y_{ij0} = {} & \beta_1 DIM_{ij0} + \beta_2 SP_{ij0} + \beta_3 EXP_{ij0} + \beta_4 DIV_{ij0} + \beta_5 P_{j0} + \beta_6 INC_{j0} + \\ & + \beta_7 AEDU_{j0} + \beta_8 Inf_{j0} + \beta_9 OInf_{j0} + \beta_{10} LHT_{j0} + \beta_{11} LMHT_{j0} + \\ & + \beta_{12} LMLT_{j0} + \beta_{13} LLT_{j0} + \beta_{14} LKS_{j0} + \beta_{15} LNKS_{j0} + \beta_{16} LO_{j0} + \\ & + \beta_{21} WS{\cdot}SP_{ij0} + \beta_{22} WS{\cdot}EXP_{ij0} + \beta_{23} WT{\cdot}DIV_{ij0} + \beta_{24} WT{\cdot}P_{j0} + \\ & + \beta_{25} WT{\cdot}INC_{j0} + \beta_{26} WT{\cdot}AEDU_{j0} + \beta_{27} WT{\cdot}OInf_{j0} + \beta_{28} WT{\cdot}LHT_{j0} + \\ & + \beta_{29} WT{\cdot}LMHT_{j0} + \beta_{30} WT{\cdot}LMLT_{j0} + \beta_{31} WT{\cdot}LLT_{j0} + \beta_{32} WT{\cdot}LKS_{j0} + \\ & + \beta_{33} WT{\cdot}LNKS_{j0} + \beta_{34} WT{\cdot}LO_{j0} + e \end{aligned} \quad [30]$$

Since these models do not incorporate any temporal or spatial lagged variable, they can be estimated by OLS. However, initial OLS estimations show non normality (Jarque-Bera test) for six of the seven sectors, and heteroskedasticity for five of the seven sectors (Koenker-Basset test). Furthermore, the large amount of variables leads some collinearity between the explanatory variables (Belsley, Kuh, and Welsch condition number and eigenvalues) and there are some outliers. In order to avoid these problems, we use the bayesian heteroskedastic linear model implemented by LeSage (1999). This procedure, based on the Gibbs sampler, produces estimations where normality is not required and heteroskedasticity and outliers can be controlled changing the prior[24]. Additionally, extremely collinear variables were removed from the industry estimations[25].We can estimate separate regressions for each sector or use any panel data methodology (pooled estimation or fixed effects). Theoretical framework and initial regressions suggest different coefficients for each sector. Thus, we estimate separate regressions for the seven sectors. All estimations include 267 municipalities, except the high-technology manufactures sector, where only 65 municipalities have initial and final employment. In order to control for a selection bias, we use the process in two stages by Heckman (1979)[26]. Finally, several spatial tests were calculated on the estimated models testing the possibility of lag or error specifications.

4.4. Results (I):firm characteristics

The results show evidence of agglomeration economies and diseconomies, and network economies and diseconomies.

[24] Following LeSage, we introduce a prior value of r=4. A detailed exposition of the method can be found in LeSage (1999). Four types of tests were used in order to control the convergence of the model (LeSage 1999, p.124-134).

[25] This refers to the initial percentage of the knowledge industry in the base year, highly correlated with the specialization coefficient, and the network lags of the specialization and initial percentage of the industry (correlated with the specialization), and the network lag of the education (highly correlated with the network lag of the income).

[26] First, a Probit model is estimated for explain the presence of the industry in the municipality (we use population, diversity, infrastructures, average education, average income and presence of other intensities of knowledge). We obtain the Mills ratio from this Probit: $R(Z) = (1'F(Z)) / f(Z)$, where *F(Z)* is the cumulative normal up to *Z* in standard deviations form the mean, and *f(z)* is the density of the standard normal. In the second stage, the inverse of the Mills ratio is introduced in the regression. The Mills ratio was statistically significant at 10% for Low-technology industries (p-level=0.0875) and the residual sector (0.0627). However, the coefficient is very small (-0.02 and -0.01) and no significant effect were observed on the other variables. Since this ratio resulted non-significant, we offer the estimations without it.

Regarding the firm size, this variable is negative and statistically significant[27] for the High-tech manufactures (β = -1.02), Knowledge non-intensive services (β = -0.14) and the residual sector of Other activities (β = -0.23). It is also negative but non-statistically significant for Low-tech manufactures and Knowledge intensive services, and positive but non-statistically significant for Medium-high and Medium-low technology industries. In a more disaggregated estimation, Combes (2000a, p. 349) found a negative impact of firm size for manufacture industries, that can be lower than -0.3. Some service sectors also show negative elasticities. Combes argues that this can not be strictly interpreted as absence of scale economies since a true firm production function is not estimated. Other explanations can be the life-cycle effect and that information spillovers are more important for small firms. In fact, in a "marshallian industrial district" (Becattini 1990), the small enterprises are the dominant form, generated by this "industrial atmosphere", and incorporates many advantages: dynamism, flexibility, etc. Similar to our results, Combes found that the most negative coefficients are generated in High-technology manufactures (β between -0.94 and -0.27). For East Germany, Blien and Wolf (2002, p.408) found that the negative effects appear for an establishment size above 99 employees (β = -0.10). They argue that this result is due to the delocalization process of the big industrial groups [28]. On the contrary, in a previous work on the Catalonian municipalities, Boix (2004) found positive elasticities for the firm size (between 0.07 and 0.24). A part of this effect can be due to the different industry aggregation (10 basic NACE industries) or to the different repercussion of this variable at the period used in the research (1986-1996). Deidda et al. (2002) found a global negative coefficient in the panel estimations (between -1.51 and -0.37), but in separate regressions firm size becomes positive for some industries. (wood products; coke and refined; precision and medical instruments …).

4.5. Results (II): concentration economies

4.5.1. Specialization

[27] We consider statistically significant the variables with a p-level lower than 10%. Nevertheless, we consider strongly significant p-levels lower than 5%. In all regressions, p-levels are provided in parenthesis.

[28] Note that Blien and Wolf use establishment and not firm. We think that when the information is available, the establishment is preferable to the firm. Under 99 employees the coefficients are positive and statistically significant (β = 0.08 and 0.02).

The index used as proxy for specialization (location coefficient) shows negative elasticities for all sectors, and only for the High-technology manufactures is not statistically significant. This negative coefficient is always lower than $\beta = -0.41$, and it is more negative for Medium-high industries and Knowledge-intensive services (-0.70 and -0.61). Glaeser et al. (1992), Combes (2000a) and Boix (2004) found a similar negative impact. In Glaeser et al. the coefficient is quite small (-0.12) but in Combes and in Boix it can be lower that -0.5 for some industries, and it tends to be more negative for service activities. However, for the industries analyzed in Henderson et al. (1995) and for some manufacturer sectors in Combes, specialization is positive and statistically significant[29]. De Lucio et al. separate industrial and regional specialization, finding negative elasticities for the non quadratic specification and large positive coefficients for the quadratic specification[30]. These conflictive results leads to a multiple interpretation of the coefficient, related to the existence of marshallian externalities for a small number of manufacturer industries, processes of life-cycle and processes of relocalization of the activity.

4.5.2. Competitive environment

Competitiveness is not measured in an intra-city or intra-regional environment but related to the number of export firms in the industry. This variable is positive and statistically significant for all manufacture industries and not statistically significant for service industries. The elasticity for High-technology industries is $\beta = 1.28$. For Medium-high and Medium-Low manufactures is $\beta = 0.42$. For Low-technology industries is 0.18. This can be interpreted as an important relationship between competition and productivity (higher propensity to export affects positively the employment growth) or maybe can be related to the presence of industrial district dynamics. This link is positively related to the technological intensity[31].

[29] In Henderson et al. (1995): Machinery; Electrical Machinery; Primary Metals; Transportation; Instruments; High-tech manufactures. In Combes (2002a): Gas and oil production; Distribution services of water and urban heating; Glass industry; Pharmaceutical industry; Manufacture of agricultural machinery and Machine tools; Production of industrial equipment; Manufacture of office machinery and computers; Bakery industry; Manufacture of miscellaneous food products and Beverage and alcohol; Working on wood; Industry of paper and pulp; Miscellaneous industries.

[30] However, these very large coefficients in the fist differences model (-4.72; -5.71; 36.60; 40.06) and their introduction in eight lags make suspect a possible problem of collinearity. We also estimated specialization using the separation in two different coefficients. However, results are worse and the model suffers of collineratity.

[31] Since this variable is only available for the year 2000, there are doubts about the real causality.

4.5.3. Diversity

Diversity, population and income are components of urbanization economies (Ohlin 1933; Hoover 1937)[32]. Diversity is related to the existence of information spillovers and a dynamic urban environment (Chinitz 1961; Jacobs 1969). In Glaeser et al. (1992) diversity is considered the dynamic part of urbanization economies. Regarding the estimated coefficients, two interesting results arise: first, the coefficient is positive for all sectors, but it is not statistically significant for High-technology manufactures and Knowledge-intensive services. Second, the coefficients are larger for manufacture industries (above $\beta = 0.22$) than for services or the residual sector (β lower than 0.14). This variable is positive in Glaeser et al. (above 0.91) and in Combes (between 0.12 and 0.38 for manufactures and between 0.11 and 0.63 for services). In Boix the coefficient is between 0.09 and 0.25, and it is not statistically significant for manufactures. In De Lucio et al. it is positive, with a coefficient of 0.5 for the model in levels and above 1.41 for the model in differences. On the other hand, Henderson et al. found positive effects for all sectors except machinery. In Deidda et al. it is positive for the global regressions (above 4.6 for services and statistically non significant for manufactures) although it is negative for the partial regressions on the North-Centre region.

4.5.4. Urban size

Population is one of the variables that Hoover (1937, p.93) originally associates with urbanization economies: a large size of the urban environment means a large market. However, Hoover adverts that a large urban size can also produce congestion costs (external diseconomies). Results show a negative and statistically significant coefficient for all manufacturing activities (between -0.56 and -0.29) that tends to be larger for higher levels of technology. This coefficient is also negative for Knowledge non-intensive services but shows a lower elasticity ($\beta = -0.07$). On the contrary, this coefficient is positive and statistically significant for Knowledge-intensive services ($\beta = 0.17$). Several explanations can be related to these results: first, an important part of the

[32] It is noted that the position of the authors about the use of the classical Ohlin-Hoover differentiation of the external effects (internal to the firm, localization and urbanization) is not homogeneous. Trullén is favourable to accept it but with limits. Boix argues that it is useful for teaching at basic levels but agree with Porter (1996) that it is too restrictive in advanced stages of the research. Since we do not deepen here in this discussion, we maintain in the comment of the results the dual perspective but privileging the non classical levels.

manufacture is produced for external markets, when Knowledge-intensive services are produced for a more local or regional environment and need a larger market before their generalization and diffusion along the urban system. Second, these results can be also associated with the incubator hypothesis (Hoover and Vernon 1959) where larger urban centres provide a more favourable environment for new activities at the initial stages of production. Finally, Knowledge-intensive services could need some advanced infrastructures, an institutional environment or other specific activities of support that are only located in large urban centres.

4.5.5. Income

Average personal income is also associated with the initial concept of urbanization economies in terms of purchasing power (Hoover 1937, p.91). Since manufactures are produced for a non-strictly local/regional market, it is expected for the coefficient to be not statistically significant. Indeed, p-levels are always above 0.26 for manufacture industries and the residual sector. Service sectors show a positive and large coefficient (above 0.32) that is statistically significant for Knowledge non-intensive services. For Knowledge intensive services the p-level is 0.12 in the non spatial regression, but in the spatial regression the p-level changes to 0.02 and the coefficient increases to 0.59. This suggests that an important part of the services are oriented to local consummators.

4.5.6. Infrastructures

Infrastructures are another different effect that some researchers like Camagni (1992) includes as a kind of urbanization economies. We control for two kinds of infrastructural effects: a better provision of road infrastructures and a composite indicator of "other infrastructures" which includes train stations, ports, primary schools, secondary schools, university centres and health infrastructures.

Although a positive coefficient for road infrastructures was expected for all sectors, this variable is positive and significant for High-technology industries (β = 2.47), Knowledge non intensive services (β = 0.18) and Other non classified activities (β = 0.21). It is negative and significant for Medium-high technology industries with a large coefficient (β = -0.48). An explanation for this unexpected coefficient can be the existence of spatial competition between this sector and High-tech. industries or Knowledge intensive services. In fact, when the spatial variables are introduced, the coefficient changes to -0.27 and the p-level changes to 0.94 at the same time that the coefficient of network relationship with Knowledge-intensive services changes to $\gamma = -0.86$.

On the other hand, the indicator of Other infrastructures is negative and significant for Medium-high and Medium-Low technology industries ($\beta = -0.12$ and $\beta = -0.09$) and it is positive and significant for Knowledge-intensive services ($\beta = 0.08$). However, when network variables were introduced in the spatial regressions, this variable was also significant for High-technology industries ($\beta = 0.61$) and for the Knowledge-intensive services the p-level changes to 0.13. Again, since the model is robust to collinerarity, these changes suggest spatial competition in the localization of the different types of knowledge.

4.5.7. Education

We use the average years of education of the residents in the city in order to test the effects of the human capital on employment growth[33]. However, it is also expected that high technology and knowledge activities should be related to higher levels of codified human capital while low technology and knowledge industries do not. Results show that this variable is negative and statistically significant for High-technology manufactures ($\beta = -1.87$), Low-technology manufactures ($\beta = -0.37$) and the residual sector ($\beta = -0.23$). This result suggests that a significant number of high-tech firms are not related to research and development activities but to bulk-process production and assembling. On the contrary, Knowledge-intensive activities are positively related to higher levels of education ($\beta = 0.45$ and statistically significant)[34]. Deidda et al. found that this coefficient (using the rate of superior graduates) was negative and statistically significant for manufactures ($\beta = -1.09$) and positive and statistically significant for services ($\beta = 2.80$).

[33] Since it is expected that higher levels of local human capital relate to higher levels of productivity, it is less clear when we use employment as dependent variable

[34] Another usual variable for human capital is the percentage of tertiary level education. This variable was also tested, but it not changed the interpretation of the results.

It should be noted that this coefficient presents an important limitation: it approaches codified knowledge effects, but not tacit human capital in the sense of Marshall (1920) or Arrow (1962). Although it can be argued that tacit human capital may be included in the specialization effects, we suggest that posterior researches should deal with this limitation[35].

4.5.8. Initial proportion of knowledge

A way for carry out the effects of a kind of knowledge intensity on the performance of the other categories of knowledge is the incorporation of the initial proportions of these other categories in the econometric regressions. It can be interpreted as the existence of localized knowledge spillovers from some kind of knowledge to the others, or as the existence of input-output links between the sectors, related to the knowledge intensity of the sectors. It is expected to found positive links from high knowledge and technology intensive sectors to low knowledge intensive sectors.

High-technology industries tend to show a negative effect on the other types of knowledge growth although this effect is statistically significant only for the residual sector (β = -0.02). Since this result was not expected, it can be due to the small proportion of this sector on the structure of the activities. An alternative explanation is that a high proportion of this kind of knowledge uses foreign inputs. *Medium-high technology* industries have a positive and statistically significant effect on Medium-low (β = 0.21) and *Low-technology industries* (β = 0.07). *Medium-low technology* industries have a positive and statistically significant effect on the High (β = 0.38), Medium-high (β = 0.24) and Low-technology industries (β = 0.05). Low-technology industries have a positive ant statistically effect on the *Medium-low* technology industries (β = 0.36) but negative on the residual sector (β = -0.12).

Knowledge-intensive services do not show statistically significant effects on the other local knowledge intensities and the coefficients tend to be small. *Knowledge non-intensive services* show a negative and statistically significant effect on Medium-high

[35] An additional issue it that in some sectors education is correlated with the personal income. Since out model is robust to collinearity, this is not very important (additionally, we tested that the coefficients do not change in a significant way excluding one or another variable), but in less robust models this can be problematic.

technology industries (β = -0.21) and positive on the Knowledge-intensive services (0.24). The introduction of network effects (table 4) has no important changes on the coefficients and p-levels for the manufactures and Knowledge-intensive services. However, it produces changes in the Knowledge-non intensive services where the only statistically significant effect remains in the Medium-low technology industries.

4.6. Results (III): network externalities

4.6.1. Connectivity/centrality index: indegree and outdegree

In order to capture connectivity effects like Capello (2000) and Trullén and Boix (2001) we introduce some indegree and outdegree indexes using the matrices of synergy and complementarity (table 5). This should explain if higher levels of centrality (role of subcenter), of a higher tendency to be connected with other municipalities, has a positive impact on the employment growth. We contrast this effect on the matrix of specialized flux and on the matrix of complementary flux. However, centrality and connectivity are scarcely significant[36]. *Specialized centrality* (indegree synergy) is positive and statistically significant for Medium-low technology manufactures Knowledge non-intensive services and the residual sector. However, the coefficients are very small (0.01; 0.008 and 0.007) and in two cases the p-level is above 0.09. *General centrality* (indegree complementarity) is statistically significant for Medium-low (β = 0.02) and Low technology manufactures (β = -0.01). *Specialized connectivity* (outdegree synergy) is statistically significant for Knowledge-non intensive services and the residual sector but the coefficients are very small again (β = 0.01). General connectivity is statistically significant for one single sector (the residual sector) but with a p-level of 0.098.

4.6.2. Network externalities in the cross-regressive model

Since the results using network centrality measures were scarce explicative, we estimated the cross-regressive model. According to the causal intuition, network effects

[36] In a second estimation (not provided here), the systemic coefficient was substituted by a dummy indicating if the city was an "historical subcenter" (old industrial city). However, the results were not significant (very small coefficients and statistically not significant).

may arise from the initial characteristics of the network municipalities. Initial spatial tests on the non spatial model show scarce evidence of simultaneous spatial correlation in the form of a spatial lag or a spatial error. Only the sector of Low-technology industries shows strong evidence of simultaneous spatial correlation, when in the Knowledge-non intensive services and in the residual sector this evidence is very weak. No evidence for the other sectors was found[37].

We differentiate two network matrices: specialization and complementarity. Network specialization effects can arise from the specialization of the other nodes and the number of export firms in the same kind of knowledge. Network complementarity effects can arise from diversity, size (population), income, infrastructures and initial knowledge in other knowledge sectors[38]. *Network specialization externalities* are not very related to the initial specialization of the cities (coefficients tend to be not statistically significant) whether in the Medium-high and Medium-low technology industries it is associated with the average initial amount of export firms in the specialization network (β of 0.23 and 0.14). Knowledge non-intensive services and the residual sector are negatively associated with this competitiveness proxy. Complementarity network effects are not very related to diversity, population, income and other infrastructures (although the coefficients are statistically significant at some time).

More interesting and robust are network complementarity externalities related to the initial percentage of other knowledge intensities in the municipalities of the network. *Network High-technology* industries coefficient is negative and significant for Knowledge-intensive services (γ = -0.03) whether it is positive and statistically significant for Knowledge non-intensive services (γ = 0.02). *Network Medium-high technology* industries show a coefficient negative and statistically significant for Low-technology industries (γ = -0.18) and Knowledge-intensive services (γ = -0.12). Coefficient for *Network Medium-low* industries is negative and statistically significant for High-technology industries (γ = -1.67) and the residual sector (γ = -0.10). *Network*

[37] In Boix (2004) the spatial lags of the dependent variable (using the same dependent variable) were significant in eight of the nine sectors. Nevertheless, they scarcely contributed to improve the R^2 or the Akaike criteria.

[38] Education is excluded because in the network form is highly correlated to income. To exchange income and education do not affect the other coefficients. Road infrastructures are also excluded because they were indirectly weighted.

Low-technology industries show a coefficient negative and statistically significant for services and the residual sector (γ between -0.34 and -0.11).

One of the most interesting results of the spatial model arises from the *Network-intensive services*. Although this variable is not statistically significant at local level, it is statistically significant in four sectors at network level. It is negative for High-technology industries (γ = -2.15), Low-tech industries (γ = -0.10) and Knowledge non-intensive services. It is positive and statistically significant for Medium-high technology industries (γ = 0.40). Since a negative coefficient can be interpreted as spatial competition between sectors, this positive coefficient suggests that Knowledge-intensive services provide advantages for the growth of Medium-high technology industries. *Knowledge-non intensive services* show a negative relationship with all the other sectors, although it is only significant for Medium-high (γ = -0.86) and Low-technology industries (γ = -0.42).

Finally, since the spatial tests (LM-Lag 4.98 > LM-error 2.78) suggest the existence of an additional lag on the dependent variable for Low-technology industries, a heteroskedastic bayesian regressive-regressive model was estimated for this sector (annex 4). The autoregressive parameter ρ=0.1635 is significant (p-level = 0.0148) although there is a reduction of the R^2, and the Akaike and Schwartz tests suggest evidence favourable to the initial cross-regressive model (more parsimonious). The LM-lag test also suggested a weak evidence for Medium-low technology industries, but in this case the estimated parameter ρ was not significant.

4.7. Limitations of the measurement

Although the empirical application gives some interesting results, it also presents important limitations that should be taken account in posterior researches. First, the OECD classification is an average for the OECD countries when the proportions of the R+D on VAB (and the other indicators used for this classification) differ between countries. However, it is true that the use of a common classification facilitates the comparisons. Second, we used industry disaggregated commuting data to approximate the networks of cities. Even though these data provides a feasible measure, other data like industry inter-firm calls or commercial transactions would provide a more exact design of the network. Third, employment data also offers a partial view about the stock and variation of knowledge in cities. Data about added value by knowledge industry, R+D, etc. should complete the analysis. Fourth, many of these data are preferable at establishment level in order to avoid the hypothesis used to aggregate at city level and to allow an individualized treatment of the inter-firm spillovers. Fifth, since data about capital and other inputs were not available, a labour demand model was used for the measurement of concentration and network economies. This model do not captures the labour savings coming from the capital or the technological innovations. Sixth, the results suggest more careful treatment of the intra-firm effects (differentiation between scale, scope, transaction costs and Schumpeterian innovation) and the marshallian localization effects since the specialization coefficients mainly captures saturation effects[39]. Non liniarities in the model (quadratic effects) should be also tested. Finally, it can be also interesting to use a true time-dynamic model in order to test the evolution of these effects along the time.

5. Conclusions and policy implications

The objective of this paper was to measure the impact of different kinds of knowledge and external economies on the urban growth in an intraregional context. The main hypothesis is that knowledge leads growth, and that this knowledge is related to the presence of agglomeration and network externalities in cities. We develops a methodology in three stages: firstly, we measure the amount and growth of knowledge in cities using the OCDE 2001 classification and employment data; secondly, we identify the spatial structure of the ambit of analysis (networks of cities); thirdly, we combine the GKLS-HKK-dLHG models with spatial econometric specifications in order to contrast the existence of spatially static (agglomeration) and spatially dynamic (network) external economies in an urban growth model. These methodologies use limited information and they are easily applicable to a large number of regions.

We apply this methodology to a case of study: Catalonia. Regarding the employment growth, the results show the existence of two simultaneous structural processes: a change from the manufactures to the services, and a change towards more knowledge-

[39] Viladecans (2003) provides interesting contributions to this problem.

intensive activities. The principal amount of knowledge intensive employment (manufactures and services) is concentrated in the metropolitan region of Barcelona.

Regarding the network of cities, the principal structure of the network shows a dense centre in Barcelona, a meshed-polycentric structure in the nucleus of the metropolitan region of Barcelona, and other stars, corridor and polycentric shapes along the Catalonian territory. The differentiation between high and low-knowledge network links shows different patterns in the articulation of the knowledge relationships. High-knowledge networks are concentrated in the metropolitan region of Barcelona and around the other subcentres of the network. On the contrary, the Low-knowledge network is denser and less hierarchical, suggesting different patterns of knowledge transmission.

The econometric model suggests the existence of agglomeration and network economies and diseconomies. We found very different responses of the different kinds of knowledge to the external economies. High-technology industries show a positive growth differential associated with a small firm size, export firms and infrastructures. Medium-high technology industries show a positive differential related to the export firms, urban diversity, other local specializations and the network link with centres specialized in knowledge-intensive services. The positive differential growth in Medium-low technology industries is associated with large firm size, export firms and other local specializations. Low-technology manufactures show a positive differential growth related to export firms, diversity, other local specialization and network size. Knowledge-intensive services relate their positive differential growth to the urban size, the average income and the level of education of the residents. Knowledge non-intensive services show a positive growth differential associated with diversity, average income, road infrastructures and specialization in high-tech industries in the network. Diseconomies use to be associated with specialization (life-cycle effect), urban size (except for Knowledge-intensive services) and spatial competition between sectors.

In summary, higher growth rates are associated to higher levels of technology and knowledge. The differential growth of the different kinds of knowledge is related to local and spatial factors (agglomeration and network externalities). Each knowledge sector shows a particular response to these factors. Important implications for policy design arise from these results, since suggest the more appropriate ambits and factors to foment or restring each type of knowledge, as well as where and why to locate a particular firm o industry in function of its knowledge intensity and specialization.

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Table 1. *Classification of technology and knowledge. OECD 2001. Adaptation to 2 digits.*

	Manufactures		Services	
HIG TECHNONOLOGY AND KNOWLEDGE	**High-technology industries**		**Knowledge-intensive services**	
	Office, accounting and computing machinery	30	Post and telecommunications	64
	Radio, TV and communications equipment	32	Finance and insurance	65 to 67
	Medical, precision and optical instruments	33	Business activities (not including real estate)	71 to 74
	Medium-high-technology industries		Education	80
			Health	85
	Chemicals*	24		
	Machinery and equipment, n.e.c.	29		
	Electrical machinery and apparatus, n.e.c	31		
	Motor vehicles, trailers and semi-trailers	34		
	Transport equipment**	35		
LOW TECHNONOLOGY AND KNOWLEDGE	**Medium-low-technology industries**		**Knowledge non-intensive services**	
	Coke, refined petroleum products, nuclear fuel	23	Retail and repair	50 to 52
	Rubber and plastics products	25	Hotels and restaurants	55
	Other non-metallic mineral products	26	Transport, storage and communications	61 to 63
	Basic metals	27	Real state	70
	Fabricated metal products	28	Administration, defence and social sec.	75
			Other services	90 to 99
	Low-technology industries			
	Food products, beverages and tobacco	15+16		
	Textiles, textile products, leather, footwear	17 to19		
	Wood and products of wood and cork	20		
	Pulp, paper, paper products	21		
	Printing and publishing	22		
	Manufacturing, n.e.c.	36		
	Recycling	37		

Source: OECD (2001)

* Includes (2423) Pharmaceuticals, originally in High-tech. manufactures

** Includes (353) Aircraft and spacecraft, originally in High-tech. manufactures

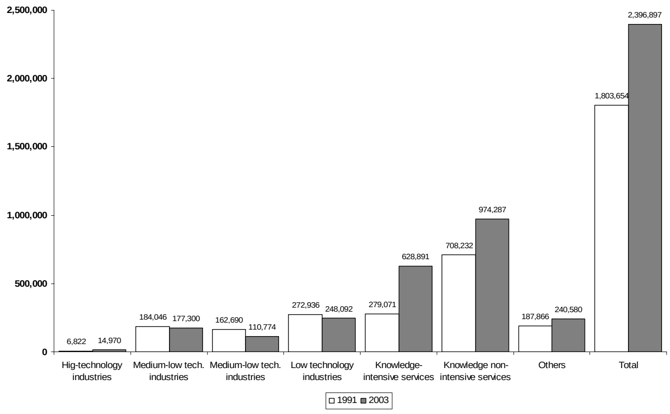
Table 2. *Activities non classified by the OECD*

Agriculture, hunting and forestry. Fishing.	01 to 05
Mining and quarrying	10 to 14
Electricity, gas and water supply	40+41
Construction	45

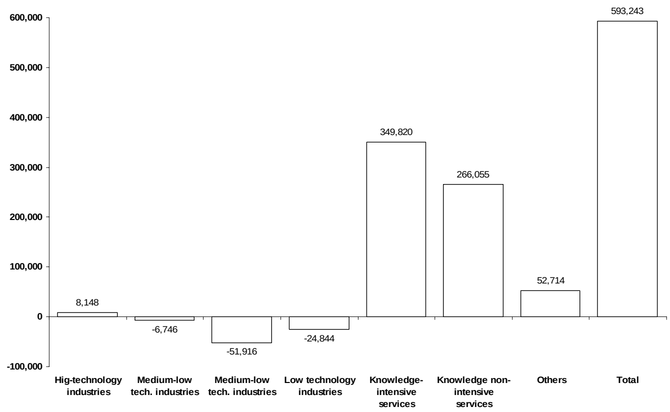
Source: OECD (2001)

Figure 1. *Employment variation by knowledge sector (1991-2003)*

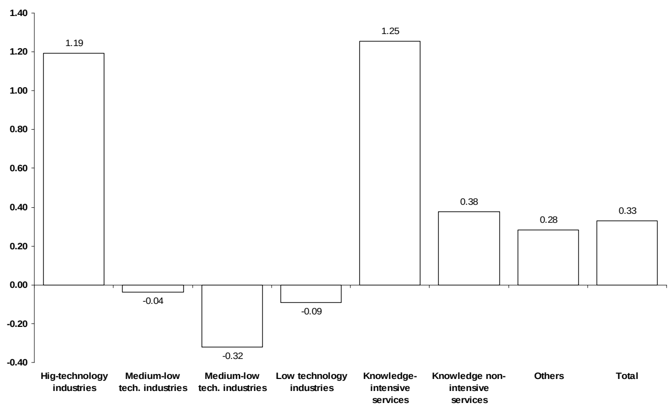
a) Employment 1991 and 2003



b) Total variation 1991-2003



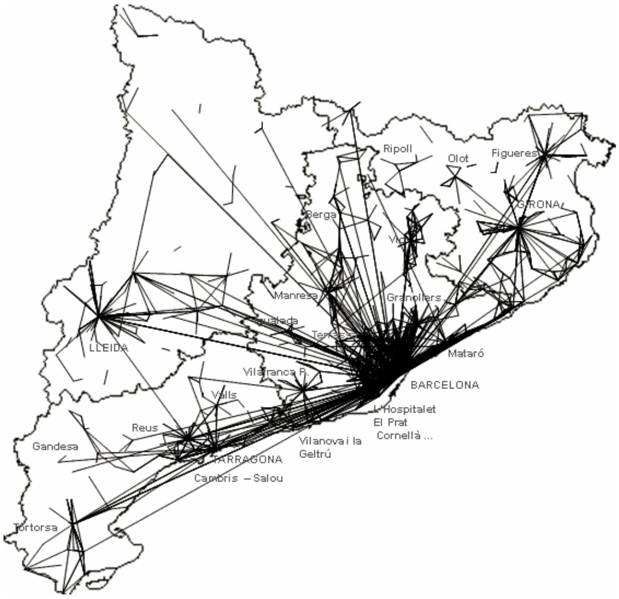
c) Growth rate 1991-2003



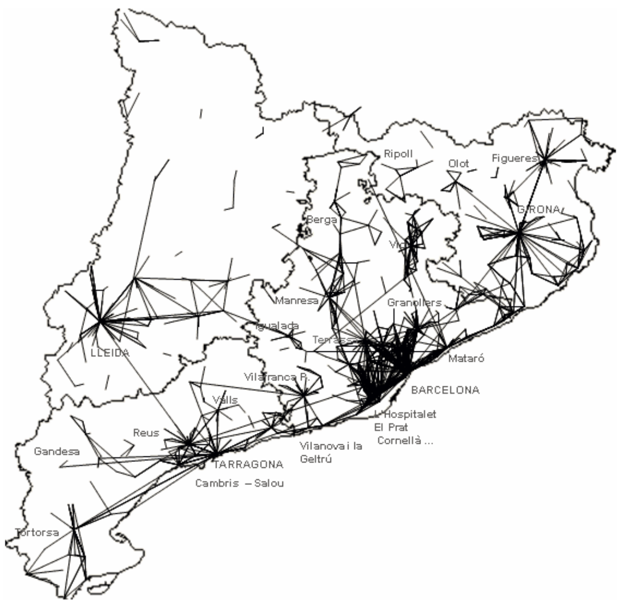
Source: Register of employees (Departament de Treball, Gencat)

Figure 2. *Networks of cities. Principal network*

a) Total



b) Without Barcelona



Source: Census 1991 (Idescat).

Figure 3. *Networks of cities by knowledge and technology*

a) High technology and knowledge networks of cities (manufactures and services)

a1.) Total

a.2) Without Barcelona

b) Low technology and knowledge networks of cities (manufactures and services)

b1.) Total

b.2) Without Barcelona

Source: Census 1991 (Idescat).

Table 3. *Dependent and explanatory variables*

Dependent variable			
- Employment (wage earners) growth rate	1991-2001	$Y_{ij0} = \ln\left(L_{ijt} / L_{ij0}\right)_j$	
Explanatory variables			
1. Firm characteristics			
• Firm size	$DIM_{ij0} = \ln\left(l_{ij0} / F_{ij0}\right)$		
2. Concentration (agglomeration) economies			
• Specialization (Location coefficient)	$SP_{ij0} = \ln\left(\dfrac{l_{ij0}/l_{i0}}{l_{j0}/l_0}\right)$	• % High-technology industries	$LHT_{j0} = \ln\left(L_{j0}^{high\,tech} / L_{j0}\right)$
• Export firms	$EXP_{ij0} = \ln(F_{ij0})$	• % Medium-high technology industries	$LMHT_{j0} = \ln\left(L_{j0}^{M-high\,tech} / L_{j0}\right)$
• Diversity (Inverse of corrected Hischmann-Herfindahl)	$DIV_{ij0} = \ln\left(1 \Big/ \sum_{j', j' \neq j}\left[\dfrac{l_{ij0}}{l_{j0}}\right]^2\right)$	• % Medium-low technology industries	$LMLT_{j0} = \ln\left(L_{j0}^{M-lowtech} / L_{j0}\right)$
• Population	$P_{j0} = \ln\left(Population_{j0}\right)$	• % Low-technology industries	$LLT_{j0} = \ln\left(L_{j0}^{lowtech} / L_{j0}\right)$
• Income	$INC_{j0} = \ln(\overline{income_{j0}})$	• % Knowledge-intensive services	$LKS_{j0} = \ln\left(L_{j0}^{know.services} / L_{j0}\right)$
• Average education (1)	$AEDU_{j0} = \ln\left(\sum A_m a_{jm0}\right)$	• % Knowledge non-intensive services	$LNKS_{j0} = \ln\left(L_{j0}^{non-know.services} / L_{j0}\right)$
• Road infrastructures	$Inf_{j0} = \ln\left(Km_{jj'0} / time_{jj'0}\right)$	• % Other non classified activities	$LO_{j0} = \ln\left(L_{j0}^{other} / L_{j0}\right)$
• Other infrastructures (2)	$OInf_{j0} = \ln\left(I_{j0}\right)$		

***Table 3** (cont.)**.** Dependent and explanatory variables*

3. Network economies

• Indegree synergy	$IS_{ij0} = \ln\left(\sum WS_{j'j0}\right)$	• WT*Other infrastructures	$WT*OInf_{j0} = WT*\ln\left(I_{j0}\right)$
• Indegree complementarity	$IC_{ij0} = \ln\left(\sum WT_{j'j0}\right)$	• WT* (% High-technology industries)	$WT*LHT_{j0} = WT*\ln\left(L_{j0}^{hightech} / L_{j0}\right)$
• Outdegree synergy	$OS_{ij0} = \ln\left(\sum WS_{jj'0}\right)$	• WT* (% Medium-high technology industries)	$WT*LMHT_{j0} = WT*\ln\left(L_{j0}^{M-hightech} / L_{j0}\right)$
• Outdegree complementarity	$OC_{ij0} = \ln\left(\sum WT_{jj'0}\right)$	• WT* (% Medium-low technology industries)	$WT*LMLT_{j0} = WT*\ln\left(L_{j0}^{M-lowtech} / L_{j0}\right)$
• WS*Specialization	$WS*SP_{ij0} = WS*\ln\left(\dfrac{l_{ij0}/l_{i0}}{l_{j0}/l_0}\right)$	• WT* (% Low-technology industries)	$WT*LLT_{j0} = \ln\left(L_{j0}^{lowtech} / L_{j0}\right)$
• WS*Export firms	$WS*EXP_{ij0} = WS*\ln(F_{ij0})$	• WT* (% Knowledge-intensive services)	$WT*LKS_{j0} = \ln\left(L_{j0}^{know.services} / L_{j0}\right)$
• WT*Diversity	$WT*DIV_{ij0} = WT*\ln\left(1 \Big/ \sum_{j',j'\neq j}\left[\dfrac{l_{ij0}}{l_{j0}}\right]^2\right)$	• WT* (% Knowledge non-intensive services)	$WT*LNKS_{j0} = WT*\ln\left(L_{j0}^{non-know.services} / L_{j0}\right)$
• WT*Population	$WT*P_{j0} = WT*\ln\left(Population_{j0}\right)$	• WT* (% Other non classified activities)	$WT*LO_{j0} = WT*\ln\left(L_{j0}^{other} / L_{j0}\right)$
• WT*Income	$WT*INC_{j0} = WT*\ln(\overline{income_{j0}})$		

L = employment; *i* = industry; *j* = city; *F* = number of firms; *Am* = number of years required for to obtain an educative level *m*; *α* = average of population above 25 years old with an educative level *m*; *WS*= intra-industry network matrix; *WC*= inter-industry network matrix.

(1) Education weights (*Am*): Individuals can read and write but with problems = 2.5; Primary education or equivalent = 5; Lowe secondary education = 8; Upper secondary and Post-secundary non tertiary education = 12; Pre-technical vocation = 10; Technical vocation = 13; First stage of tertiary education (3 years) = 15; First stage of tertiary education (4 or 5 years) and Second stage of tertiary education = 17;

(2) Other infrastructures: we consider train stations, ports, primary, secondary and university centres, hospitals, and other health infrastructures. The index is the sum of the number of types of infrastructures that can have the municipality (minimum = 0; maximum = 7).

Table 4. *Non spatial model. Bayesian Heteroskedastic Linear Model Gibbs Estimates.*

Dependent variable: Ln Employment growth rate

	High-tech. industries	Medium-high tech. industries	Medium-low tech. industries	Low-tech. industries	Knowledge intensive services	Knowledge non-intensive services	Other non classified activities
Ln Firm size	**-1.0208** ***	0.0851	0.1316	-0.0490	-0.0227	**-0.1416** **	**-0.2329** ***
	(0.0001)	(0.2354)	(0.1335)	(0.2568)	(0.4058)	(0.0291)	(0.0000)
Ln Specialization	-0.1424	**-0.7057** ***	**-0.5713** ***	**-0.4504** ***	**-0.6163** ***	**-0.5036** ***	**-0.4138** ***
	(0.2439)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln Export firms	**1.2822** ***	**0.4297** ***	**0.4297** ***	**0.1826** ***	-0.1202	0.0358	-0.0332
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.1306)	(0.1532)	(0.3033)
Ln Diversity	0.6469	**0.4998** ***	**0.2289** *	**0.3635** ***	0.0933	**0.1396** ***	**0.0877** *
	(0.169)	(0.0029)	(0.0611)	(0.0000)	(0.2544)	(0.0069)	(0.0863)
Ln Population	**-0.5692** ***	**-0.3541** ***	**-0.2576** ***	**-0.2912** ***	**0.1745** ***	**-0.0718** **	-0.0298
	(0.0031)	(0.0000)	(0.0001)	(0.0000)	(0.0006)	(0.0133)	(0.1826)
Ln Income	0.5639	0.2164	-0.2319	0.0469	0.3218	**0.3982** ***	-0.0449
	(0.3844)	(0.2995)	(0.2676)	(0.4085)	(0.1282)	(0.0021)	(0.4204)
Ln Road infrastructures	**2.4796** ***	**-0.4804** ***	0.1105	-0.0461	0.1325	**0.1865** ***	**0.2193** ***
	(0.001)	(0.0091)	(0.2893)	(0.331)	(0.1751)	(0.0069)	(0.0083)
Ln Other infrastructures	0.2070	**-0.1201** **	**-0.0927** **	0.0377	**0.0797** **	0.0165	0.0010
	(0.2356)	(0.0285)	(0.0306)	(0.1243)	(0.0487)	(0.1934)	(0.4762)
Ln Education	**-1.8765** *	0.0023	-0.1657	**-0.3711** ***	**0.4553** ***	0.0220	**-0.2363** **
	(0.0724)	(0.5013)	(0.2563)	(0.0057)	(0.0065)	(0.4095)	(0.0272)
Ln Rate of self-employment	-0.7871	**-0.2968** **	-0.1366	**-0.2987** ***	-0.0061	**-0.1150** *	**-0.1263** *
	(0.1621)	(0.0428)	(0.2245)	(0.0026)	(0.4888)	(0.0649)	(0.0639)
Ln % High-tech. industries	-	-0.0098	-0.0113	0.0007	-0.0025	0.0005	**-0.0203** ***
		(0.2865)	(0.2488)	(0.4752)	(0.4206)	(0.4756)	(0.003)
Ln % Medium-high tech. industries	0.0121	-	**0.2138** ***	**0.0749** ***	0.0342	0.0014	-0.0168
	(0.486)		(0.0000)	(0.0069)	(0.2112)	(0.4733)	(0.2376)
Ln % Medium-low tech. industries	**0.3851** *	**0.2493** ***	-	**0.0550** **	-0.0013	-0.0211	-0.0236
	(0.0872)	(0.0001)		(0.0483)	(0.4929)	(0.1839)	(0.1970)
Ln % Low-tech. industries	-0.0060	-0.0154	**0.3683** ***	-	0.0474	-0.0373	**-0.1282** ***
	(0.4871)	(0.4258)	(0.0000)		(0.2262)	(0.1000)	(0.0003)
Ln % Knowledge intensive services	0.1697	-0.0768	-0.0379	0.0061	-	0.0022	-0.0226
	(0.2512)	(0.1219)	(0.2895)	(0.4398)		(0.4722)	(0.2267)
Ln % Knowledge non-intensive services	-0.5007	**-0.2161** *	0.1616	-0.0120	**0.2411** **	-	0.0177
	(0.2831)	(0.0974)	(0.1507)	(0.4467)	(0.0444)		(0.4089)

Ln % Other non classified activities	-0.5133	0.0441	0.0970	0.0805	**0.1183** *	**0.0539** *	-
	(0.1174)	(0.3407)	(0.1806)	(0.1121)	(0.0707)	(0.0941)	
R^2	0.6797	0.4591	0.3985	0.4183	0.4807	0.4182	0.3892
R^2-adj	0.5816	0.4268	0.3626	0.3835	0.4497	0.3835	0.3527
σ^2	0.7253	0.4779	0.4406	0.1477	0.2389	0.0642	0.0933
RSS	55.5758	211.4654	190.6453	65.1504	115.8046	27.4028	51.2302
AIC	0.3357	-0.1133	-0.2170	-1.2907	-0.7155	-2.1568	-1.5311
SC	4.0177	5.3541	5.2504	4.1767	4.7519	3.3106	3.9363
Moran I (synergy matrix)	-	-0.8895	0.1338	2.1663 **	-0.7240	-1.0759	-0.7804
LM-Error (synergy matrix)	-	0.9658	0.0017	4.2247 **	0.4252	1.2817	0.6930
LR-Error (synergy matrix)	-	1.2411	0.0024	5.5579 **	0.7624	1.5670	0.9335
Wald-Error (synergy matrix)	-	0.5989	0.0019	3.3943 *	0.3854	0.6791	0.4169
LM-Lag (synergy matrix)	-	0.6909	0.2256	1.9831	0.6417	3.6522 *	3.5297 *
LM-Lag LE (synergy matrix)	-	0.0048	0.9674	0.5846	0.2340	2.7210 *	4.3827 **
SARMA (synergy matrix)	-	0.9706	0.9691	4.8094 *	0.6592	4.0027	5.0757 *
Moran I (complem. matrix)	0.2483	-0.2265	-0.0244	0.2757	-0.8910	-0.7614	0.4554
LM-Error (complem. matrix)	0.0020	0.1838	1.7148	0.1662	1.5660	0.3529	0.0065
LR-Error (complem. matrix)	0.0054	0.2447	1.5922	0.2105	1.8818	0.3720	0.0070
Wald-Error (complem. matrix)	0.0035	0.1178	0.6246	0.0939	0.8293	0.1770	0.0032
LM-Lag (complem. matrix)	0.7236	0.0001	2.7029	3.4677 *	0.0575	0.1592	0.1874
LM-Lag LE (complem. matrix)	1.6534	0.3821	1.0128	8.9220 ***	2.3826	0.0148	0.8331
SARMA (complem. matrix)	1.6554	0.5659	2.7276	9.0882 **	3.9487	0.3677	0.8396
Obs	65	267	267	267	267	267	267

Prior r= 4. Draws = 10,000. Data in parenthesis are p-levels. Significance: 1% (***); 5% (**); 10% (*).

Table 5. *Subcenter model. Bayesian Heteroskedastic Linear Model Gibbs Estimates.*

Dependent variable: Ln Employment growth rate

	High-tech. industries	Medium-high tech. industries	Medium-low tech. industries	Low-tech. industries	Knowledge intensive services	Knowledge non-intensive services	Other non classified activities
Ln Firm size	**-0.9926** ***	0.0927	0.1271	-0.0271	-0.0074	**-0.1032** *	**-0.2200** ***
	(0.0000)	(0.2217)	(0.1493)	(0.3627)	(0.4674)	(0.0808)	(0.0000)
Ln Specialization	-0.1793	**-0.7206** ***	**-0.5748** ***	**-0.5144** ***	**-0.6317** ***	**-0.5962** ***	**-0.4354** ***
	(0.2015)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln Export firms	**1.2861** ***	**0.4339** ***	**0.4024** ***	**0.1813** ***	-0.1157	0.0403	-0.0198
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.1431)	(0.1337)	(0.3815)
Ln Diversity	0.7450	**0.4858** ***	0.1932	**0.3594** ***	0.1009	**0.1356** ***	**0.1060** *
	(0.1597)	(0.0035)	(0.1015)	(0.0000)	(0.2461)	(0.0068)	(0.0538)
Ln Population	**-0.7469** ***	**-0.3490** ***	**-0.3418** ***	**-0.2480** ***	**0.1479** **	**-0.1084** ***	**-0.0835** **
	(0.0043)	(0.0000)	(0.0000)	(0.0000)	(0.0175)	(0.0014)	(0.014)
Ln Income	0.4582	0.2282	-0.3525	0.0821	0.2604	**0.3318** ***	-0.0958
	(0.4095)	(0.2887)	(0.1778)	(0.3519)	(0.1926)	(0.008)	(0.3168)
Ln Road infrastructures	**2.5573** ***	**-0.4690** ***	0.0662	0.0380	0.1071	**0.1421** **	**0.1698** **
	(0.001)	(0.0098)	(0.3619)	(0.3718)	(0.2379)	(0.0278)	(0.0357)
Ln Other infrastructures	0.2560	**-0.1187** **	**-0.1002** **	0.0368	**0.0857** **	0.0227	0.0080
	(0.1886)	(0.0301)	(0.0279)	(0.1578)	(0.0472)	(0.1147)	(0.3690)
Ln Education	**-1.8292** *	0.0227	-0.1613	**-0.3358** **	**0.4084** **	-0.0366	**-0.2304** **
	(0.0821)	(0.4677)	(0.26)	(0.0108)	(0.0173)	(0.3549)	(0.0305)
Ln Rate of self-employment	-0.9152	**-0.2684** *	-0.1760	**-0.2815** ***	-0.0263	**-0.1003** *	**-0.1235** *
	(0.1405)	(0.0630)	(0.1744)	(0.0047)	(0.4219)	(0.0820)	(0.0738)
Ln % High-tech. industries	-	-0.0120	-0.0102	-0.0031	-0.0025	0.0020	**-0.0175** ***
		(0.2408)	(0.2684)	(0.3641)	(0.4211)	(0.3692)	(0.008)
Ln % Medium-high tech. industries	-0.0406	-	**0.2057** ***	**0.0735** ***	0.0354	0.0028	-0.0194
	(0.4434)		(0.0001)	(0.0058)	(0.2041)	(0.4448)	(0.2144)
Ln % Medium-low tech. industries	0.3440	**0.2443** ***	-	**0.0832** ***	-0.0096	-0.0244	-0.0347
	(0.1184)	(0.0001)		(0.0076)	(0.4285)	(0.1455)	(0.1125)
Ln % Low-tech. industries	-0.0366	-0.0111	**0.3639** ***	-	0.0353	-0.0254	**-0.1268** ***
	(0.4626)	(0.4426)	(0.0000)		(0.2956)	(0.1808)	(0.0002)
Ln % Knowledge intensive services	0.2020	-0.0784	-0.0034	0.0013	-	0.0140	-0.0196
	(0.2065)	(0.1185)	(0.4823)	(0.4861)		(0.2744)	(0.2514)

Ln % Knowledge non-intensive services	-0.6116	-0.2109	0.1517	0.0019	**0.2122** *	-	-0.0285
	(0.2496)	(0.1029)	(0.1744)	(0.4906)	(0.0798)		(0.3539)
Ln % Other non classified activities	-0.6955	0.0429	0.1350	**0.0868** *	**0.1175** *	**0.0765** **	-
	(0.1001)	(0.354)	(0.1042)	(0.0965)	(0.0777)	(0.0257)	
Indegree synergy	-	-0.0026	**0.0191** *	0.0072	0.0078	**0.0084** *	**0.0072** *
		(0.4349)	(0.0926)	(0.1838)	(0.2496)	(0.0518)	(0.0983)
Indegree complementarity	-0.1262	-0.0075	**0.0280** *	**-0.0194** **	-0.0040	-0.0061	0.0033
	(0.3667)	(0.3386)	(0.0609)	(0.0195)	(0.3844)	(0.1807)	(0.3332)
Outdegree synergy	-	0.0112	0.0001	0.0032	0.0083	**0.0154** ***	**0.0108** **
		(0.2197)	(0.4994)	(0.3296)	(0.1942)	(0.0003)	(0.0242)
Outdegree complementarity	0.3378	0.0009	0.0194	-0.0132	-0.0026	0.0066	**0.0116** *
	(0.1144)	(0.4864)	(0.2117)	(0.1037)	(0.4479)	(0.2076)	(0.0980)
R^2	0.6882	0.4603	0.4061	0.4373	0.4837	0.4559	0.4251
R^2-adj	0.5755	0.4188	0.3605	0.394	0.444	0.4141	0.3809
σ^2	0.7275	0.4854	0.4355	0.1459	0.2415	0.0608	0.0925
RSS	54.0925	210.9899	188.2284	63.0220	115.1272	25.6272	48.2195
AIC	0.3702	-0.0856	-0.1998	-1.2940	-0.6914	-2.1938	-1.5617
SC	3.9907	5.3518	5.2377	4.1435	4.7460	3.2437	3.8758
Moran I (synergy matrix)	-	-0.7610	0.1786	2.3454 **	-0.5856	-0.5522	-0.0376
LM-Error (synergy matrix)	-	0.7748	0.0077	4.9018 **	0.2646	0.3851	0.0099
LR-Error (synergy matrix)	-	1.0601	0.0121	6.8354 ***	0.4796	0.5059	0.0144
Wald-Error (synergy matrix)	-	0.5170	0.0058	4.3045 **	0.2215	0.2229	0.0071
LM-Lag (synergy matrix)	-	0.4669	0.3097	2.9515 *	0.1277	0.0557	1.7468
LM-Lag LE (synergy matrix)	-	0.0079	1.2016	0.2001	0.1036	0.1689	3.9755 **
SARMA (synergy matrix)	-	0.7826	1.2094	5.1020 *	0.3683	0.5539	3.9855
Moran I (complem. matrix)	0.4002	-0.2001	-0.1020	0.4141	-0.8566	-1.1216	0.4601
LM-Error (complem. matrix)	0.0033	0.1796	1.7479	0.4210	0.9221	0.0026	0.0877
LR-Error (complem. matrix)	0.0089	0.2436	1.7334	0.4940	1.2541	0.0037	0.0975
Wald-Error (complem. matrix)	0.0070	0.1177	0.6937	0.2040	0.5460	0.0023	0.0397
LM-Lag (complem. matrix)	0.9526	0.0030	2.8084	4.6852 **	0.0036	0.2971	0.7849
LM-Lag LE (complem. matrix)	2.0434	0.2877	1.0767	10.4596 ***	2.7549	0.8666	1.1347
SARMA (complem. matrix)	2.0468	0.4674	2.8246	10.8806 ***	3.6770	0.8692	1.2224
Obs	65	267	267	267	267	267	267

Prior r= 4. Draws = 10,000. Data in parenthesis are p-levels. Significance: 1% (***); 5% (**); 10% (*).

Table 6. *Cross regressive spatial model. Bayesian Heteroskedastic Linear Model Gibbs Estimates.*

Dependent variable: Ln Employment growth rate

	High-tech. industries	Medium-high tech. industries	Medium-low tech. industries	Low-tech. industries	Knowledge intensive services	Knowledge non-intensive services	Other non classified activities
Ln Firm size	**-1.1608 *****	0.0578	**0.1851 ***	-0.0031	-0.0609	**-0.1297 ****	**-0.2327 *****
	(0.0001)	(0.3096)	(0.0681)	(0.4848)	(0.2547)	(0.0373)	(0.0000)
Ln Specialization	0.0134	**-0.6873 *****	**-0.6000 *****	**-0.5310 *****	**-0.6281 *****	**-0.5165 *****	**-0.4109 *****
	(0.4753)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln Export firms	**1.5111 *****	**0.4204 *****	**0.3942 *****	**0.1845 *****	-0.1301	0.0378	0.0032
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.1135)	(0.1468)	(0.4885)
Ln Diversity	0.3665	**0.4342 *****	0.1515	**0.4356 *****	0.1469	**0.1545 *****	0.0828
	(0.2955)	(0.0066)	(0.1568)	(0.0000)	(0.1424)	(0.0046)	(0.1138)
Ln Population	**-0.7325 *****	**-0.3061 *****	**-0.2741 *****	**-0.2842 *****	**0.1973 *****	**-0.0980 *****	-0.0298
	(0.0003)	(0.0004)	(0.0001)	(0.0000)	(0.0008)	(0.0022)	(0.1918)
Ln Income	1.7871	0.0904	-0.4943	0.0045	**0.5993 ****	**0.3033 ****	-0.0822
	(0.1823)	(0.4226)	(0.1098)	(0.4936)	(0.0228)	(0.0234)	(0.3508)
Ln Road infrastructures	**3.1042 *****	**-0.2748 ***	0.1419	-0.0011	0.1119	**0.1483 ****	**0.2032 ****
	(0.0002)	(0.0944)	(0.2461)	(0.495)	(0.2276)	(0.0351)	(0.0184)
Ln Other infrastructures	**0.6199 ***	**-0.1134 ****	**-0.0848 ***	0.0148	0.0535	0.0230	-0.0178
	(0.0808)	(0.0375)	(0.0598)	(0.3122)	(0.1309)	(0.1248)	(0.2858)
Ln Education	**-3.3139 ****	0.0363	-0.2383	**-0.3767 *****	**0.3620 ****	0.0189	**-0.2388 ****
	(0.0111)	(0.4466)	(0.1835)	(0.0083)	(0.0330)	(0.4234)	(0.0262)
Ln Rate of self-employment	**-1.3076 ***	**-0.2613 ***	-0.0752	**-0.2741 *****	-0.0589	**-0.1371 ****	-0.1051
	(0.0566)	(0.0701)	(0.3440)	(0.0032)	(0.3144)	(0.0435)	(0.1027)
Ln % High-tech. industries	-	-0.0151	-0.0092	0.0014	-0.0035	0.0024	**-0.0171 ****
		(0.1970)	(0.2994)	(0.4414)	(0.3836)	(0.3464)	(0.0125)
Ln % Medium-high tech. industries	0.0265	-	**0.2083 *****	**0.0697 ****	0.0341	0.0088	-0.0126
	(0.4663)		(0.0001)	(0.0102)	(0.2095)	(0.334)	(0.2982)
Ln % Medium-low tech. industries	**0.4552 ***	**0.2790 *****	-	**0.0733 ****	-0.0042	-0.0184	-0.0092
	(0.0607)	(0.0000)		(0.0207)	(0.4689)	(0.2242)	(0.3739)
Ln % Low-tech. industries	-0.0822	-0.0296	**0.3501 *****	-	0.0812	-0.0091	**-0.0930 *****
	(0.4275)	(0.3680)	(0.0002)		(0.1262)	(0.3877)	(0.0099)
Ln % Knowledge intensive services	0.2600	-0.0647	-0.0200	-0.0063	-	0.0011	-0.0292
	(0.1434)	(0.1586)	(0.3854)	(0.4306)		(0.482)	(0.1610)

	High-tech. industries	Medium-high tech. industries	Medium-low tech. industries	Low-tech. industries	Knowledge intensive services	Knowledge non-intensive services	Other non classified activities
Ln % Knowledge non-intensive services	-0.8484	-0.1778	**0.2246 ***	0.0170	0.1668	-	0.0182
	(0.1881)	(0.1370)	(0.0790)	(0.4169)	(0.1244)		(0.4096)
Ln % Other non classified activities	-0.1035	0.0531	0.0963	**0.1426 ****	0.1023	0.0477	-
	(0.4099)	(0.3228)	(0.1852)	(0.0166)	(0.1064)	(0.1313)	
WS* Ln Specialization	-	**-0.2798 ***	-0.0082	0.0693	-0.0419	0.0692	0.0880
		(0.0833)	(0.4878)	(0.2692)	(0.3392)	(0.2376)	(0.2245)
WS * Ln Export firms	-	**0.2323 ****	**0.1432 ***	0.0200	0.0174	**-0.0293 ***	**0.0503 ***
		(0.0158)	(0.0682)	(0.3252)	(0.3690)	(0.0580)	(0.0752)
WT* Ln Diversity	**2.8593 ***	0.3177	-0.1874	-0.0916	0.2266	-0.0928	-0.0739
	(0.0917)	(0.1898)	(0.2685)	(0.3079)	(0.2014)	(0.1630)	(0.2859)
WT* Ln Population	0.3690	-0.0773	0.0515	**0.0922 ****	0.0708	0.0311	-0.0004
	(0.1499)	(0.1540)	(0.2406)	(0.0264)	(0.1037)	(0.1661)	(0.4970)
WT* Ln Income	**-6.4343 ***	-0.8833	0.7845	-0.0845	**-0.7455 ***	0.2108	0.4100
	(0.0591)	(0.1456)	(0.1575)	(0.4311)	(0.0991)	(0.2248)	(0.1211)
WT* Ln Other infrastructures	-0.0809	0.0212	0.0084	0.0587	-0.0587	0.0386	0.0433
	(0.4499)	(0.4396)	(0.4772)	(0.2382)	(0.2737)	(0.2400)	(0.2536)
WT* Ln % High-tech. industries	-	-0.0112	0.0297	0.0066	**-0.0385 ****	**0.0214 ****	-0.0016
		(0.3597)	(0.1734)	(0.3601)	(0.0461)	(0.0377)	(0.4553)
WT* Ln % Medium-high tech. industries	0.4386	-	0.0632	**-0.1856 *****	**-0.1286 ***	0.0117	0.0114
	(0.2929)		(0.2826)	(0.0006)	(0.0656)	(0.3888)	(0.3992)
WT* Ln % Medium-low tech. industries	**-1.6767 ****	-0.0968	-	-0.0549	-0.0455	-0.0040	**-0.1071 ****
	(0.0417)	(0.2574)		(0.2297)	(0.3149)	(0.4648)	(0.0321)
WT* Ln % Low-tech. industries	-0.9998	0.0171	0.0285	-	**-0.3455 *****	**-0.1148 ****	**-0.1483 ****
	(0.1088)	(0.4631)	(0.4387)		(0.0082)	(0.0329)	(0.0245)
WT* Ln % Knowledge intensive services	**-2.1521 ****	**0.4013 *****	-0.0143	**-0.1006 ***	-	**-0.0856 ***	-0.0050
	(0.0133)	(0.0010)	(0.4593)	(0.0947)		(0.0534)	(0.4690)
WT* Ln % Knowledge non-intensive services	-2.9914	**-0.8680 ****	-0.4762	**-0.4227 ****	-0.3400	-	-0.1881
	(0.1605)	(0.0156)	(0.1037)	(0.0132)	(0.1431)		(0.1384)
WT* Ln % Other non classified activities	1.2174	-0.0911	**0.3093 ***	-0.1586	**-0.2861 ****	0.0885	-
	(0.1772)	(0.3411)	(0.0906)	(0.1131)	(0.0341)	(0.1419)	

	High-tech. industries	Medium-high tech. industries	Medium-low tech. industries	Low-tech. industries	Knowledge intensive services	Knowledge non-intensive services	Other non classified activities
R^2	0.7786	0.4927	0.4137	0.4674	0.5065	0.4451	0.4252
R^2-adj	0.6367	0.4354	0.3475	0.4072	0.4507	0.3824	0.3603
σ^2	0.5971	0.4637	0.4342	0.1384	0.2356	0.0615	0.0915
RSS	38.4111	198.3232	185.8372	59.6490	110.0539	26.1369	48.2111
AIC	0.2739	-0.0876	-0.1526	-1.2890	-0.6765	-2.1141	-1.5019
SC	3.6483	5.2898	5.2248	4.0884	4.7009	3.2633	3.8755
Moran I (synergy matrix)	-	1.0016	0.3954	1.9671 *	0.3995	-1.2596	0.1717
LM-Error (synergy matrix)	-	1.3596	0.0282	2.7877 *	0.0942	1.6855	0.0001
LR-Error (synergy matrix)	-	2.0900	0.0455	3.8533 **	0.1772	2.5375	0.0001
Wald-Error (synergy matrix)	-	1.0995	0.0249	2.0638	0.0884	1.2151	0.0003
LM-Lag (synergy matrix)	-	1.1609	0.2711	4.9860 **	0.1058	2.1922	0.3103
LM-Lag LE (synergy matrix)	-	0.0366	0.8049	2.7680 *	0.0132	0.5505	1.7193
SARMA (synergy matrix)	-	1.3962	0.8331	5.5557 *	0.1074	2.2361	1.7194
Moran I (complem. matrix)	1.0877	0.0671	0.0222	0.4092	-0.6688	-0.7963	0.4627
LM-Error (complem. matrix)	0.1348	0.6983	1.1816	0.1134	0.9736	0.8585	0.2408
LR-Error (complem. matrix)	0.3278	1.1009	1.4742	0.1633	1.3643	1.0012	0.3073
Wald-Error (complem. matrix)	0.1847	0.5273	0.6593	0.0783	0.6613	0.3869	0.1367
LM-Lag (complem. matrix)	0.9732	0.6323	2.9310 *	1.7286	0.1338	0.3719	0.1123
LM-Lag LE (complem. matrix)	2.1201	0.0303	2.7736 *	11.3025 ***	1.1530	0.2114	2.6656
SARMA (complem. matrix)	2.2549	0.7287	3.9552	11.4159 ***	2.1267	1.0700	2.9064
Obs	65	267	267	267	267	267	267

Prior r= 4. Draws = 20,000. Data in parenthesis are p-levels. Significance: 1% (***); 5% (**); 10% (*).

Annex I.

II.1. Manufactures by intensity of technology and knowledge

a) High-technology industries

Total

Without Barcelona

b) Médium-high-technology industries

Total

Without Barcelona

c) Médium-low-technology industries

Total

Without Barcelona

d) Low-technology industries

Total *Without Barcelona*

II.2. Services by intensity of technology and knowledge

a) Knowledge-intensive services

Total *Without Barcelona*

b) Knowledge non-intensive services

Total *Without Barcelona*

Source: Census 1991 (Idescat).

II.c. Non-classified activities: primary sector, extractives, energy and water, and building.

Total

Without Barcelona

Source: Census 1991 (Idescat).

Annex III. Descriptive statistics (variables in logarithms)

High-tech. industries

	Mean	Mediana	Stand.desv.	Obs
Y	0.6852	0.7940	1.6465	65
Firm size	2.1376	2.0369	1.1863	65
Specialization	-0.1460	-0.0462	1.3713	65
Export firms	0.7387	0.6931	0.7512	65
Diversity	3.9162	3.9886	0.3212	65
Population	10.0186	10.1795	1.3751	65
Income	7.7228	7.6875	0.1430	65
Road infras.	0.2513	0.2108	0.1910	65
Other infras..	0.8433	0.6931	0.4560	65
Education	2.3690	2.3550	0.2067	65
Self employ.	4.4301	4.4461	0.1768	65
% HT ind.	-1.0315	-0.9875	1.4326	65
% MHT ind.	2.2617	2.3973	0.8881	65
% MLT ind.	2.4079	2.5074	0.7490	65
% LT ind.	2.7498	2.7895	0.5799	65
% KIS	1.9055	2.0657	0.9713	65
% KnIS	3.4647	3.4756	0.3327	65
% Other	2.1867	2.2270	0.4715	65
Indegree Sp.	-9.2103	-9.2103	0.0000	65
Indegree Co.	2.7307	2.7726	0.9666	65
Outdegree S.	-9.2103	-9.2103	0.0000	65
Outdegree C.	2.6382	2.7726	0.9183	65

Medium-high tech. industries

	Mean	Mediana	Stand.desv.	Obs
Y	0.3659	0.3062	1.2123	267
Firm size	2.4133	2.4129	1.0795	267
Specialization	-0.7236	-0.6741	1.2778	267
Export firms	0.8987	0.6931	0.9733	267
Diversity	3.5385	3.6217	0.5204	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	0.0000	-0.0119	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-6.0470	-9.2103	4.7419	267
Indegree Co.	0.4491	1.3863	3.5694	267
Outdegree S.	-6.8457	-9.2103	4.3777	267
Outdegree C.	1.0881	1.6095	2.5936	267

Medium-low tech. industries

	Mean	Mediana	Stand.desv.	Obs
Y	-0.2024	-0.1361	1.0916	267
Firm size	2.1180	2.1745	0.8456	267
Specialization	-0.2077	-0.1129	1.0348	267
Export firms	0.6322	0.0000	0.8760	267
Diversity	3.5612	3.6226	0.5521	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	4.4526	4.4407	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-5.7419	-9.2103	4.8166	267
Indegree Co.	0.4067	1.3863	3.6184	267
Outdegree S.	-6.6373	-9.2103	4.4768	267
Outdegree C.	1.0604	1.6095	2.6018	267

Low-tech. industries

	Mean	Mediana	Stand.desv.	Obs
Y	0.0831	0.0663	0.6489	267
Firm size	2.3467	2.3843	0.7108	267
Specialization	0.1432	0.2539	0.8967	267
Export firms	1.0787	1.0986	0.9778	267
Diversity	3.7431	3.8312	0.5612	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	4.4526	4.4407	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-3.0728	0.0001	4.9826	267
Indegree Co.	-0.6925	0.6932	4.4656	267
Outdegree S.	-3.1016	0.0001	4.9608	267
Outdegree C.	0.1536	1.0986	3.6615	267

Knowledge intensive services

	Mean	Mediana	Stand.desv.	Obs
Y	1.1270	1.0296	0.9156	267
Firm size	1.4637	1.4966	0.7349	267
Specialization	-1.4653	-1.2935	1.1856	267
Export firms	0.1228	0.0000	0.4027	267
Diversity	3.4876	3.5853	0.5060	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	4.4526	4.4407	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-5.3959	-9.2103	4.8567	267
Indegree Co.	0.4504	1.3863	3.5705	267
Outdegree S.	-5.7968	-9.2103	4.7859	267
Outdegree C.	1.0657	1.3863	2.5178	267

Knowledge non-intensive services

	Mean	Mediana	Stand.desv.	Obs
Y	0.6460	0.5992	0.4208	267
Firm size	1.5047	1.4391	0.4573	267
Specialization	-0.4984	-0.4828	0.4865	267
Export firms	0.8207	0.6931	0.9874	267
Diversity	3.4870	3.5392	0.5977	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	4.4526	4.4407	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-4.8577	-9.2103	5.0492	267
Indegree Co.	0.4164	1.3863	3.5040	267
Outdegree S.	-3.8755	0.0001	5.0079	267
Outdegree C.	0.7126	1.3863	3.0610	267

Other non classified activities

	Mean	Mediana	Stand.desv.	Obs
Y	0.5138	0.5187	0.5615	267
Firm size	1.2206	1.2777	0.7100	267
Specialization	0.0902	0.1013	0.7215	267
Export firms	0.1373	0.0000	0.3740	267
Diversity	3.6540	3.8097	0.5678	267
Population	8.7539	8.5348	1.2268	267
Income	7.6362	7.6217	0.1742	267
Road infras.	0.1514	0.1754	0.2691	267
Other infras..	0.4754	0.6931	1.1352	267
Education	2.2657	2.2734	0.2717	267
Self employ.	4.4526	4.4407	0.3030	267
% HT ind.	-6.8331	-9.2103	3.8156	267
% MHT ind.	1.7013	1.8353	1.2638	267
% MLT ind.	2.0939	2.2104	1.0108	267
% LT ind.	2.9622	3.1095	0.8455	267
% KIS	1.3759	1.6176	1.1552	267
% KnIS	3.2741	3.3118	0.4987	267
% Other	2.5357	2.5464	0.6961	267
Indegree Sp.	-3.5364	0.0001	4.9858	267
Indegree Co.	-0.1645	1.3863	4.1352	267
Outdegree S.	-3.3283	0.0001	4.9715	267
Outdegree C.	0.4955	1.3863	3.3292	267

Annex IV. Regressive-regressive spatial model for Low-technology industries. Bayesian Heteroskedastic Linear Estimation.

Dependent variable: Ln Employment growth rate

Ln Firm size	-0.0015	WS* Ln Specialization	0.0796
	(0.4959)		(0.2292)
Ln Specialization	**-0.5278*** **	WS * Ln Export firms	0.0312
	(0.0000)		(0.2286)
Ln Export firms	**0.1703*** **	WT* Ln Diversity	-0.1177
	(0.0001)		(0.2602)
Ln Diversity	**0.4367*** **	WT* Ln Population	**0.0925** **
	(0.0000)		(0.0237)
Ln Population	**-0.2711*** **	WT* Ln Income	-0.0148
	(0.0000)		(0.492)
Ln Income	0.0303	WT* Ln Other infrastructures	0.0575
	(0.4466)		(0.2397)
Ln Road infrastructures	-0.0065	WT* Ln % High-tech. industries	0.0057
	(0.4772)		(0.3778)
Ln Other infrastructures	0.0101	WT* Ln % Medium-high tech. industries	**-0.1981*** **
	(0.3643)		(0.0004)
Ln Education	**-0.3745*** **	WT* Ln % Medium-low tech. industries	-0.0431
	(0.0093)		(0.2794)
Ln Rate of self-employment	**-0.2743*** **	WT* Ln % Low-tech. industries	-
	(0.0032)		
Ln % High-tech. industries	0.0013	WT* Ln % Knowledge intensive services	-0.0803
	(0.443)		(0.1467)
Ln % Medium-high tech. industries	**0.0685*** **	WT* Ln % Knowledge non-intensive services	**-0.4384*** **
	(0.0094)		(0.0083)
Ln % Medium-low tech. industries	**0.0706** **	WT* Ln % Other non classified activities	-0.1636*
	(0.0191)		(0.0987)
Ln % Low-tech. industries	-	ρ	**0.1635** **
			(0.0148)
Ln % Knowledge intensive services	-0.0127	R^2	0.4095
	(0.3608)	R^2-adj	0.3428
Ln % Knowledge non-intensive services	0.0142	RSS	66.1321
	(0.4306)	AIC	-1.1858
Ln % Other non classified activities	**0.1364** **	SC	4.1916
	(0.0191)	Obs	267

Prior r= 4. Draws = 20,000. Data in parenthesis are p-levels. Significance: 1% (***); 5% (**); 10% (*).