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Departament d'Economia Aplicada  
Edifici B  
Campus de Bellaterra  
08193 Bellaterra

Telèfon: (93) 581 1680  
Fax:(93) 581 2292  
E-mail: [d.econ.aplicada@uab.es](mailto:d.econ.aplicada@uab.es)  
<http://www.ecap.uab.es>

## **Knowledge, networks of cities and growth in regional urban systems**

**Joan Trullén and Rafael Boix<sup>1</sup>**

Departament d'Economia Aplicada, Universitat Autònoma de Barcelona.

Edifici B, 08193 Bellaterra (Barcelona). Spain.

Tfn. 0034 93 5812244 / 0034 93 5811528 Fax. 93 5812292

e-mail: joan.trullen@uab.es / rafael.boix@uab.es

**Abstract:** The objective of this paper is to measure the impact of different kinds of knowledge and external economies on urban growth in an intraregional context. The main hypothesis is that knowledge leads to growth, and that this knowledge is related to the existence of agglomeration and network externalities in cities. We develop a three-stage methodology: first, we measure the amount and growth of knowledge in cities using the OCDE (2003) classification and employment data; second, we identify the spatial structure of the area of analysis (networks of cities); third, we combine the Glaeser - Henderson - De Lucio 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. Results suggest that higher growth rates are associated to higher levels of technology and knowledge. The growth of the different kinds of knowledge is related to local and spatial factors (agglomeration and network externalities) and each knowledge intensity shows a particular response to these factors. These results have implications for policy design, since we can forecast and intervene on local knowledge development paths.

**JEL:** R11, R12, O3

**Keywords:** Knowledge city, networks of cities, urban growth, external economies, spatial econometrics.

### **1. Introduction**

Marshall (1890, Book IV Chapter I.1) explains that “the agents of production are commonly classed as Land, Labour and Capital”. Capital is the main stock of wealth regarded as an agent of production rather than a direct source of gratification. Capital consists in a great part of knowledge and organization. Knowledge is our most powerful engine of production. Organization aids knowledge and when public and private property in knowledge and organization are distinguished, organization can be considered a distinct agent of production (Marshall 1890). A hundred years later, Romer

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(1986, 1990) remarks that knowledge is the main determinant of economic growth. The main characteristic of knowledge is that it is a non-rival good, because the utilization of knowledge by one actor does not reduce the quantity available for another actor. This lack of rivalry implies the possibility of increasing returns in the production function. In Romer's model, imperfect competition is needed in order to remunerate knowledge accumulation (Schumpeterian framework).

However, knowledge accumulation can also occur as an accidental product generated from the actors' activity in the economy (Jones 1998). In this case, knowledge accumulation can arise from the existence of external economies. There is a spatial nexus between knowledge, external economies, and growth. Knowledge is not dispersed but is concentrated in urban units as cities and metropolitan areas (Knight 1995). The concentration of actors in the same urban units leads to the generation of externalities producing knowledge spillovers. This merged capacity to concentrate and generate knowledge, organization, and external economies transforms the city into the most powerful of the productive artefacts.

Cities are not isolated systems but rather are linked to other cities forming networks. A network of cities is a structure where the nodes are the cities, connected by different kinds of links through which socioeconomic flows are exchanged through communication and telecommunication infrastructures. Links between cities can be specified using information and knowledge flows. This approach permits the analysis of the processes of generation and diffusion of knowledge through the urban structure. Contrarily to Central Place Models (Webber 1972), in the modern *network paradigm* knowledge diffusion cannot only be performed in a vertical way, but also among cities of the same rank and from cities of lower rank to cities of higher rank<sup>2</sup>. Thus, the existence of stable relational channels between cities can also generate knowledge spillovers (Pred 1977) and the third and fourth of Marshall's factors of production appears in a spatial form.

## **2. Knowledge measurement in cities and identification of knowledge-based networks of cities**

### *2.1. Methodology*

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<sup>2</sup> 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 organization and exchanges between cities.

### 2.1.1. Knowledge measurement in cities

The OECD (2003) provides certain indicators that are applied on a country-level. Several of these indicators are based on adaptations of the activities and skills classifications (ISIC, ISCO). According to the OECD (2003), manufactures can be aggregated on four levels of technological intensity: high, medium-high, medium-low and low; and services on two levels of knowledge: intensive knowledge and non-intensive knowledge. In a residual sector, we include the activities not classified by the OECD (Primary activities; Extractives; Energy and water; and Construction). Although this classification needs three digits of information, it can be adapted to two digits with a small loss of precision (table 1). We propose the use of this classification on employment data in order to construct a city-level indicator of knowledge. Although this indicator is a partial approximation to the city knowledge base, it has the advantage that employment data by industry is usually available on a municipal level and that it allows for the creation of a time series and international comparison.

Table 1. Classification of technology and knowledge. OECD 2003. Adaptation to 2 digits.

	<b>Manufactures</b>	<b>Services and other activities</b>
<b>HIG TECHNOLOGY AND KNOWLEDGE</b>	<b>High-technology industries</b>	<b>Knowledge-intensive services</b>
	30 Office, accounting and computing machinery	64 Post and telecommunications
	32 Radio, TV and communications equipment	65 to 67 Finance and insurance
	33 Medical, precision and optical instruments	71 to 74 Business activities (not including real estate)
	<b>Medium-high-technology industries</b>	80 Education
	24 Chemicals*	85 Health
	29 Machinery and equipment, n.e.c.	
	31 Electrical machinery and apparatus, n.e.c	
	34 Motor vehicles, trailers and semi-trailers	
	35 Transport equipment**	
<b>LOW TECHNOLOGY AND KNOWLEDGE</b>	<b>Medium-low-technology industries</b>	<b>Knowledge non-intensive services</b>
	23 Coke, refined petroleum products, nuclear fuel	50 to 52 Retail and repair
	25 Rubber and plastics products	55 Hotels and restaurants
	26 Other non-metallic mineral products	61 to 63 Transport, storage and communications
	27 Basic metals	70 Real state
	28 Fabricated metal products	75 Administration, defence and social sec.
		90 to 99 Other services
	<b>Low-technology industries</b>	<b>Other activities non classified by the OECD (Residual industries)</b>
	15+16 Food products, beverages and tobacco	01 to 05 Agriculture, hunting and forestry. Fishing.
	17 to19 Textiles, textile products, leather, footwear	10 to 14 Mining and quarrying
	20 Wood and products of wood and cork	40+41 Electricity, gas and water supply
	21 Pulp, paper, paper products	45 Construction
	22 Printing and publishing	
36 Manufacturing, n.e.c.		
37 Recycling		

Source: Authors' own work based on OECD (2003)

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

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

### 2.1.2. Identification of knowledge-based networks of cities

The little research into the identification of networks of cities has generally been of a heterogeneous nature. This heterogeneity arises from the different objectives of the research and the availability of data. This makes it very difficult to compare the results of the different investigations. We distinguish two types of methodologies. *Indirect methodologies* try to identify networks of cities using dynamized stock data or by contrasting the differences with the Christallerian model (Dematteis 1989; Camagni and Salone 1993). *Direct methodologies* are based on the direct use of flows: there is a network link between two urban units 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 but interaction in all of its forms (Pred 1977; Boix 2002).

Since no other data are available, we use commuting data (home to work) to identify the structure of the network. These data are related not only to residential choices but also to social relations and infrastructural endowments. In previous research, (Boix 2002) we proved the capacity of this kind of flow to reveal the urban structure<sup>3</sup>. However, they are an imperfect indicator of knowledge links. A feasible hypothesis is that these flows could be important when the municipality of origin and the destination municipality contain a significant amount of employees in the activities under study, and the flow is larger than the mean<sup>4</sup>. 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:

$$FSC_{i,j}^s = \frac{F_{i,j}^s}{F^s} \bigg/ \frac{F_i}{F} \quad (1)$$

, where  $F$  = external commuting flow;  $s$  = sector (industry);  $i$  = origin city;  $j$  = destination city. An FSC coefficient above 1 indicates relative specialization in the structure of fluxes. We apply a filter above 1.25. Additionally, two restrictions are imposed in order to remove non-significant or stochastic behaviour in the smaller

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<sup>3</sup> In a regional context, commuting flows are strongly correlated with telephonic and retail flows. For a meticulous study of the productive relations, additional types of flows (such as interfirm transactions) would be preferable.

<sup>4</sup> In 2001, there were 1,285,000 inter-municipality commuters in 42,000 pairs of connexions City A → City B. However, there is a large amount of low quantity flows that tend to be of little significance for the detection of urban structure. Thus, if a filter above 50 commuters is applied only 3,159 pairs of connexions remain that embrace 1,070,000 commuters. This means that 82% of commuters move in 7.5% of the intermunicipal relationships.

municipalities: a minimum flow of 10 commuters and that the flux accounts for a minimum of 1% of the total jobs in the city. An asymmetric binary matrix is obtained for each industry, where a value of 1 indicates that there is a network link between two municipalities.

The FSC imposes a double restriction: the emitting city would be relatively specialised in the sector related to its labour force, and the attractor city would be relatively specialised in the sector in order to originate a differential of attraction. The FSC is applied using the OECD knowledge classification on data taken from the 1991 and 2001 Censuses. It is possible to identify the networks using the aggregate data for the seven groups of knowledge. However, it is also possible to apply the FSC to each industry within each knowledge group. The latter is advisable in order to differentiate particular behaviours and to obtain an asymmetric weighted matrix for each knowledge group.

## *2.2. Results of knowledge measurement and network identification*

### *2.2.1. Results of knowledge measurement*

We use the municipality (city or town) as the spatial unit of analysis. This is not an ideal unit but it complies with two main conditions (Sforzi 1999): it is isolable for analysis and is a tool for the interpretation of the economic reality. Additionally, it offers two advantages: it is a disaggregated nodal urban unit and it has administrative autonomy. Catalonia contains 6,350,000 inhabitants distributed across 944 municipalities. Around 80% of the population lives in units of more than 10,000 inhabitants (10% of the municipalities). The largest city is Barcelona, which contains 1.5 million inhabitants and 30% of the employment of Catalonia. The more important cities are located in the Metropolitan Region of Barcelona, around old industrial subcentres and along motorway corridors.

We apply the indicator based on the OECD classification to the municipalities of Catalonia. We use wage-earning employees taken from Social Security data from between 1991 and 2003. In 2003, High Technology Manufactures (HTM) contained 15,000 employees, Medium-High Technology Manufactures (MHTM) contained 177,000 employees; Medium-Low Technology Manufactures (MLTM) contained 111,000 employees, Knowledge Intensive Services (KIS) contained 629,000 employees, Knowledge non-Intensive Services (KnIS) contained 975,000 employees, and the Residual Sector (RS) contained 240,000 employees. This means that high-knowledge

activities contained 34% of the employment, low-knowledge activities contained 56% and the residual sector contained 10% of the employment.

The growth rate for wage-earning employment is 33%. We observe two opposing trends (table 2): HTM (119%), KIS (125%), KnIS (38%) and RS (28%) increased the number of employees, while MHTM (-4%), MLTM (-32%) and LTM decreased (-9%). The most dynamic activities by municipality (activities with the highest growth rate) are KnIS (38% of municipalities), KIS (26% of municipalities) and RS (24% of municipalities). However, there is distortion due to the existence of a large amount of micro-municipalities. By isolating those municipalities with more than 1,000 inhabitants, the results change drastically: KIS are the most dynamic activities (50% of municipalities), followed by MHTM (12% of municipalities) and HTM (11% of municipalities). On the contrary, LTM (4% of municipalities) and MLTM (3% of municipalities) are the least dynamic activities.

Regarding the territorial distribution of employment, the main amount of high and medium-high technology and knowledge activities (manufactures and services) is concentrated in the centre of the Metropolitan Region of Barcelona and in other medium cities such as Tarragona, Reus, Girona and Lleida. Low and medium-low technology and knowledge activities are distributed around 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.

Table 2. Growth rate by technology and knowledge intensity. 1991-2003

	Catalonia	Percentage of times that it has the highest growth rate in a municipality	Percentage of times that it has the highest growth rate. Municipalities $\geq$ 1,000 inhabitants
High-tech. manufactures	1%	8%	11%
Medium-high tech. manufactures	-1%	13%	12%
Medium-low tech. manufactures	-9%	10%	3%
Low tech. manufactures	-4%	14%	4%
Knowledge intensive services	59%	26%	50%
Knowledge non intensive services	45%	38%	9%
Residual sector	9%	24%	9%
Total	33%	100%	100%

Source: Authors' own work based on the Labour Department of Gencat, Idescat and OECD (2003)

We can conclude that, although low knowledge activities continue to have a dominant share on the employment structure, three simultaneous processes can be detected: first, a change from manufactures to services; second, a change towards more



knowledge intensive activities; third, a concentration of knowledge intensive activities in large and medium cities located in the metropolitan areas combined with a relocation of manufacturing activities.

### *2.2.2. Results of the identification of knowledge-based networks of cities*

Figure 1 shows the main network relationships in the Catalonian city system. The city of Barcelona is the main 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 appear as star-shaped structures that are typical of central place models (the networks of Girona, Lleida and Vilafranca del Penedès). The networks of Igualada, Manresa and Vic combine polarized structures with a trend to expand along the motorway corridors towards the centre of the metropolitan region of Barcelona.

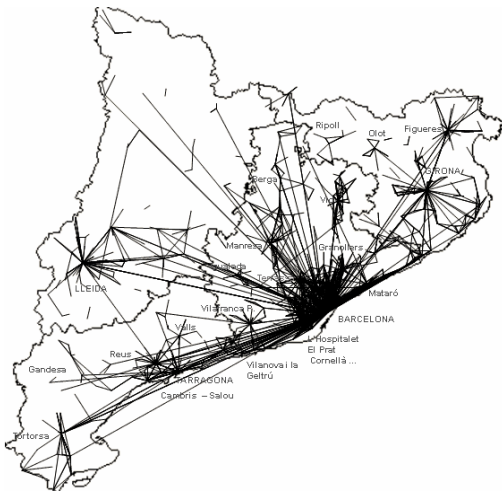
Differentiating high and low knowledge networks (figure 1b and 1c), two different patterns appear. A large amount of High-knowledge networks arise from the link with Barcelona (the city with highest levels of knowledge in the network). Removing Barcelona, we observe that the other high-knowledge network 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 is less hierarchical, with a meshed-polycentric centre in the core of the metropolitan region of Barcelona, stars around Lleida, Girona-Figuera, Vilafranca del Penedès and Igualada, a polycentric structure in Tarragona-Reus-Valls and some mixed pole-corridor structures around Manresa and Vic.

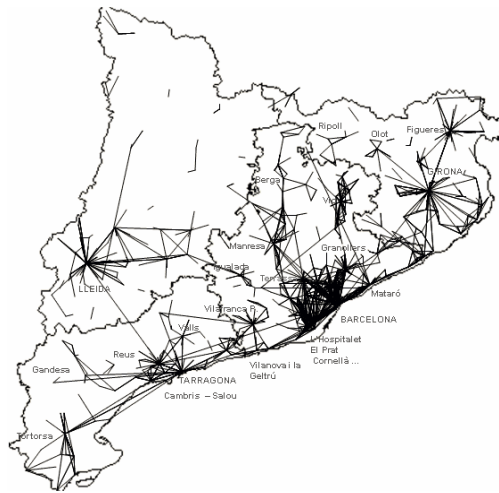
Figure 1. Networks of cities by knowledge and technology

a) *Main network*

a1.) Total



a.2) Without Barcelona



b) *High technology and knowledge networks of cities (manufactures and services)*

b1.) Total



b.2) Without Barcelona



c) *Low technology and knowledge networks of cities (manufactures and services)*

c1.) Total



c.2) Without Barcelona



Source: Authors' own work based on 1991 Census (Idescat) and OECD (2003)

### **3. Modelling the effects of knowledge and external economies on urban growth**

Two main approaches arise when knowledge or innovation are the objectives of the research (Autant-Bernard and Massard 1999). The first 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 in R&D, and innovations introduced to the market<sup>5</sup>. The second approach is based on the effects of knowledge and innovation on efficiency/productivity or on economic growth. The theoretical framework is based on the endogenous growth theory (Solow 1957, Arrow 1962, Lucas 1988, Romer 1986 and 1990). Empirical applications use production, productivity or employment growth as dependent variables, and knowledge or innovation are modelled within the production function. The most influential research into urban economics are Glaeser, Kallal, Scheikman and Shleifer (1992) and Henderson, Kunkoro and Turner (1995). Other interesting contributions centred on knowledge and externalities are Deidda, Paci and Usai (2002) and De Lucio, Herce and Goicolea (2002). A critical vision of the limitations of these approaches is provided by Breschi and Lissoni (2001).

Other issues appear in the empirical implementation of both approaches. First, since initial productivity/efficiency measurements were temporally static, the temporal dimension typical of growth models was highlighted after Glaeser et al. (1992) and Henderson et al. (1995). However, these models continued to be spatially static. The rise of spatial econometrics (Anselin, 1988) and the development of specific software (SpaceStat) facilitated the introduction of space, mainly in the knowledge/innovation production function approach, sometimes called the “spillover approach”. Second, the unit of analysis changes depending of the availability of information: information about regions, metropolitan areas, labour markets, cities and firms. The latter is preferred because it avoids aggregation bias, but it is not usually available and can present problems related to censure, truncation or unknown sample selection. When no information on firms is available, the use of urban units (cities, metropolitan areas) or labour markets is preferred. Finally, the availability of data affects the choice of the dependent variable (production/productivity or employment) and the number of effects tested.

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<sup>5</sup> Autant-Bernard and Massard (1999) provide a critical review.

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

There is an important limitation related to information on a city level: it is very difficult to obtain production and capital data aggregated by city or for a large enough sample of firms. We describe three models that avoid this problem. On the basis of these models, we can estimate agglomeration and network economies.

1. Glaeser et al. (1992) derive a function of growth starting from a function of labour demand without capital data. They suppose a firm in a certain industry and in a location with a production function dependent on technology  $A_t f(l_t)$  (2), where  $A$  represents changes in the level of technology and prices,  $l_t$  is the labour input and  $t$  is the time period<sup>6</sup>. Each firm in each industry takes as given the technology, prices and wages ( $w_t$ ), and maximizes  $\Phi = A_t f(l_t) - w_t l_t$  (3). This equals the marginal product of labour with its price, which is the wage:  $A_t f'(l_t) = w_t$  (4). The equation is expressed as growth rates and linearized using logarithms. Under the hypothesis that the level of technology in a city-industry is the product of the local and national components:  $A = A_{local} \cdot A_{national}$  (5), changes in technology and prices depend on a local and a national component. The growth rate of the local 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:

$$\alpha \log\left(\frac{l_{t+1}}{l_t}\right) = -\log\left(\frac{w_{t+1}}{w_t}\right) + \log\left(\frac{A_{national,t+1}}{A_{national,t}}\right) + g(\cdot) + u_{t+1} \quad (6)$$

2. 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 time  $t$  is  $\Phi = A_{it} f(N_{it}; \dots)$  (7), where  $N$  is employment and  $A$  the level of technology. The equilibrium employment level for an industry  $j$  in a city  $i$  at time  $t$  equals the marginal product of the input:  $W_{it} = A_{it}(\cdot) f'(N_{it}; \dots) P_{it}(\cdot)$  (8), where  $W$  is the nominal wage rate,  $P$  is the price of output given a downward sloping inverse demand function  $P_{it}(\cdot) = P(N_{it}; MC_{it})$  (9), and  $MC$  are the regional characteristics. Again, the hypothesis is that  $A_{it}$  is a function of the externalities in the base year. Substituting  $A(\cdot)$  and  $P(\cdot)$  in the equation of equilibrium (equation 8), inverting and assuming that the changes in the technology depend on initial conditions, we obtain the reduced-form

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<sup>6</sup> It allows for technological and pecuniary externalities, but only those derived from labour.

equation:  $N_{it} = N(N_{i0}, W_{i0}, MC_{i0}, g_{i0})$  (10). 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. De Lucio et al. (2002) introduce a firm Cobb-Douglas function and endogenously derive the index to measure knowledge externalities:  $Y_{ijt} = A_{ijt} L_{ijt}^\alpha K_{ijt}^\beta$  (11), where  $\alpha, \beta$  are the labour and capital coefficients, assumed to be constant. After the maximization and linearization of the production function, we obtain a model where factor prices are endogenous. 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 endogenized, 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:  $dA_{ijt}/dt = A_{ijt}^*(g_0)$  (12), where  $g$  is a vector of explanatory variables including external economies. Resolving the differential equation we obtain:  $\ln(Y_{ijt}/Y_{ij0}) = \beta_0 + \beta_1 \ln(L_{ijt}/L_{ij0}) + \beta_2 \ln(W_{ijt}/W_{ij0}) + \beta_3 \ln(\phi_{ijt}/\phi_{ij0}) + g(\cdot)$  (13), where  $\phi$  is the productivity. If there is not enough information available, we can assume a functional form with one input  $\Phi = A_{ijt} L_{ijt}^{1-\alpha}$  (14), and the model will be similar to Glaeser et al. (1992) and Henderson et al. (1995).

These specifications allow for the estimation of a production function with one (or several) inputs in a temporally dynamic framework. We can incorporate two transformations to the final equation. First, since our area 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<sup>7</sup>. 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 such as a premium on wages:  $W_{ijt}/W_{ij0} = (1 + \theta)(w_{ijt}/w_{ij0})$  (15), where  $W$  is the nominal wage,  $w$  is the real wage and  $\theta$  is the premium due to externalities. Under this assumption, the wage can be removed when separate industry estimations or intra-groups estimators are performed

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<sup>7</sup> This hypothesis is also suggested in Glaeser et al. (1992, p. 1134). Indeed, this is confirmed when the authors use wage growth as the dependent variable in their estimations. In our empirical application to Catalonia wage growth is fixed in a regional negotiation.

(demeaned equation)<sup>8</sup>. The same will be true for the interest rate. Then, the term  $\theta$  will be incorporated into the vector of external effects  $g$ .

Second, the aforementioned 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 confront with the assumption of the exogeneity of technology and prices. Glaeser et al. (1992) partially avoid this problem by including the inverse of a firm size vector such as a competition index. Combes (2000a) argues that in the endogenous growth model spirit, large plants will be penalized if internal returns decrease. An alternative explanation arises from the importance and dynamism of small firms in growth processes as suggested by Becattini (1990).

The demeaned GKSS model takes the form:  $[y - \bar{y}] = [f(\cdot) - \bar{f}(\cdot)] + [g(\cdot) - \bar{g}(\cdot)] + u$  (16), or taking  $y^* = [y - \bar{y}]$ ,  $f^* = [f(\cdot) - \bar{f}(\cdot)]$  and  $g^* = [g(\cdot) - \bar{g}(\cdot)]$ , we obtain:  $y^* = f(\cdot)^* + g(\cdot)^* + u$  (17), where  $y = \alpha \log(l_{t+1}/l_t)$ ,  $f(\cdot)$  is a vector of the characteristics of the firm, and  $g(\cdot)$  is a vector of external economies that incorporates knowledge and non-knowledge externalities (dynamic and static in GKSS nomenclature). This demeaned equation can be estimated in the usual form:  $y = X\beta + u$ , excluding the constant term (Johnston and Dinardo 1997).

### 3.2 Extension to a spatially dynamic framework

The assumption that technology depends on certain local and national factors is too general. It neglects the mechanisms of generation, transmission, adoption and feedback of externalities and knowledge through the urban system. We will consider that technology depends on 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 obtained using a model of distribution of new innovations like De Lucio et al. (2002). Spatial econometrics (Anselin 1988) provides an easy method for dealing with the specification of this network extension. Network relationships can be incorporated using a matrix of spatial contacts  $W$ . This matrix

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<sup>8</sup> Other research, like Combes (2000a), acts in a similar way by not including wages in its estimations.

corresponds to the knowledge-based networks identified in section 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*:  $y = X\beta + WX\gamma + u$  (18)<sup>9</sup>.

## 4. Econometric measurement

### 4.1. Database and sample

The data used in the estimations comes from several databases: firms, wage earner employment and self-employment (Labour Department, INSS and Gencat)<sup>10</sup>; export firms (Exporters Yearbook from Acicsa); population and education levels by age (Census from Idescat); average income by municipality (Department of Economy and Idescat); travel time and distance between municipalities (GIS optimization); primary, secondary and university education centres (Gencat Department of Education), health centres (hospitals and other health centres from the Gencat Department of Health ); ports and airports (several Gencat departments); and commuting (travel to work) by municipality and industry (Census from Idescat). Employment, firms and commuting data are available by industry and municipality. Population, average income, education, and infrastructure data are used on a municipal level. The data were aggregated in seven groups using the OECD (2003) knowledge classification.

The first issue to be addressed is the definition of the relevant unit of analysis for the econometric estimations. Although Catalonia is composed of 944 municipalities, a large number of these are micro-municipalities. This will lead to a problem associated with the number of zeros by industry and another related to outliers. We decided to define as relevant economic units those municipalities that have employment in six of the seven macro-sectors in the analysis. This led to the use of a sample of 267 municipalities as relevant urban units. These units include 96% of wage earning employment for the years 1991 and 2003 (1,734,186 and 2,277,842 employees) and

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<sup>9</sup> Other options can be taken into account since knowledge externalities can arise from the simultaneous growth of the sector in the other cities of the network (*spatial lag model*), from the network lags of the dependent and explanatory variables (*regressive-regressive spatial model*) or from stochastic shocks throughout the network of cities (*spatial error model*). All these models can be combined to produce a family of spatial models (Anselin 1988) or extended to more complex specifications. These models enable the simultaneous estimation of concentration (agglomeration) and network externalities. Otherwise, it is possible to ascertain if network effects are not significant.

<sup>10</sup> Gencat is the acronym for the Generalitat de Catalunya (the regional government) and Idescat is the Catalanian Institute of Statistics.

explains the 96.6% of the total variation in wage earning employment (543,656 employees to 563,003)<sup>11</sup>. Additionally, we will test for a possible selection bias.

#### 4.2. Variables

Following the modified model shown in section 3, we will estimate a labour demand equation without factor prices (because these 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 wage earning employment between 1991 and 2003. The explanatory variables were divided into three sets: firm characteristics, concentration economies and network economies (table 3).

Firm characteristics include the inverse of the firm size relating the existence of small firms to a dynamic environment (Marshall - Becattini approach). This variable can be negative indicating that growth is related to the scale of the firm (Schumpeterian approach). Glaeser et al. (1992) and Combes (2000a) argue that in the presence of decreasing returns (competitive market) there will be a negative relationship between firm size and growth.

Concentration (agglomeration economies) includes most of the factors expressed in the literature on external economies: Marshall (1890), Ohlin (1993), Hoover (1937), Chinitz (1961), Jacobs (1969), Porter (1996) and Camagni (1992). This includes specialization effects (location coefficient), international competition (number of export firms), diversity (inverse of the Hirschmann-Herfindahl index), population and income (market size and depth), 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 for the initial year<sup>12</sup>. Finally, the growth rate of self-employment is included in order to correct its effect on salaried employment. Following the theoretical model, all variables were expressed in logarithms<sup>13</sup>.

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<sup>11</sup> A less restrictive option could be the aggregation of the other municipalities as supra-municipal units. However, there would still be a considerable amount of zeros.

<sup>12</sup> The percentage of each sector is excluded because it is included in the specialization index. Including it again would cause strong collinearity.

<sup>13</sup> Note that the usual variable of initial employment level is not included. Combes (2000b) argues that the inclusion of this variable leads to endogeneity and changes the interpretation of the location coefficient. Furthermore, in some sectors it is highly correlated with population.



Table 3. Dependent and explanatory variables

<b>DEPENDENT VARIABLE:</b> Employment (wage earners) growth rate 1991-2001 $Y_{j0} = \ln(L_{jt}/L_{j0})_j$			
<b>EXPLANATORY VARIABLES</b>			
<b>Firm characteristics</b>		<b>Network economies: subcentres</b>	
Small firm size	$SDIM_{j0} = \ln\left[1/\left(I_{j0}/F_{j0}\right)\right]$	Indegree synergy	$IS_{j0} = \ln\left(\sum WS_{j'j0}\right)$
		Indegree complementarity	$IC_{j0} = \ln\left(\sum WT_{j'j0}\right)$
<b>Concentration (agglomeration) economies</b>		Outdegree synergy	$OS_{j0} = \ln\left(\sum WS_{jj0}\right)$
Specialization (Location coefficient)	$SP_{j0} = \ln\left(\frac{I_{j0}/I_{j0}}{I_{j0}/I_{j0}}\right)$	Outdegree complementarity	$OC_{j0} = \ln\left(\sum WT_{jj0}\right)$
Export firms	$EXP_{j0} = \ln(F_{j0})$	<b>Network economies: synergy and complementarity</b>	
Diversity (Inverse of corrected Hirschmann-Herfindahl)	$DIV_{j0} = \ln\left(1/\sum_{j,j'}\left[\frac{I_{j0}}{I_{j0}}\right]^2\right)$	WS*Specialization	$WS_0 * SP_{j0} = WS_0 * \ln\left(\frac{I_{j0}/I_{j0}}{I_{j0}/I_{j0}}\right)$
Population	$P_{j0} = \ln(Population_{j0})$	WS*Export firms	$WS_0 * EXP_{j0} = WS_0 * \ln(F_{j0})$
Income	$INC_{j0} = \ln(\overline{income}_{j0})$	WT*Diversity	$WT_0 * DIV_{j0} = WT_0 * \ln\left(1/\sum_{j,j'}\left[\frac{I_{j0}}{I_{j0}}\right]^2\right)$
Average education <sup>(1)</sup>	$AEDU_{j0} = \ln\left(\sum A_m \alpha_{m0}\right)$	WT*Population	$WT_0 * P_{j0} = WT_0 * \ln(Population_{j0})$
Road infrastructures	$Inf_{j0} = \ln(Km_{j'0}/time_{j'0})$	WT*Income	$WT_0 * INC_{j0} = WT_0 * \ln(\overline{income}_{j0})$
Other infrastructures <sup>(2)</sup>	$OInf_{j0} = \ln(I_{j0})$	WT*Other infrastructures	$WT_0 * OInf_{j0} = WT_0 * \ln(I_{j0})$
% High-technology industries	$LHT_{j0} = \ln(L_{j0}^{HT}/L_{j0})$	WT* (% High-technology industries)	$WT_0 * LHT_{j0} = WT_0 * \ln(L_{j0}^{HT}/L_{j0})$
% Medium-high technology industries	$LMHT_{j0} = \ln(L_{j0}^{MHT}/L_{j0})$	WT* (% Medium-high technology industries)	$WT_0 * LMHT_{j0} = WT_0 * \ln(L_{j0}^{MHT}/L_{j0})$
% Medium-low technology industries	$LMLT_{j0} = \ln(L_{j0}^{MLT}/L_{j0})$	WT* (% Medium-low technology industries)	$WT_0 * LMLT_{j0} = WT_0 * \ln(L_{j0}^{MLT}/L_{j0})$
% Low-technology industries	$LLT_{j0} = \ln(L_{j0}^{LT}/L_{j0})$	WT* (% Low-technology industries)	$WT_0 * LLT_{j0} = WT_0 * \ln(L_{j0}^{LT}/L_{j0})$
% Knowledge-intensive services	$LKS_{j0} = \ln(L_{j0}^{KIS}/L_{j0})$	WT* (% Knowledge-intensive services)	$WT_0 * LKIS_{j0} = WT_0 * \ln(L_{j0}^{KIS}/L_{j0})$
% Knowledge non-intensive services	$LNKS_{j0} = \ln(L_{j0}^{NKIS}/L_{j0})$	WT* (% Knowledge non-intensive services)	$WT_0 * LNKIS_{j0} = WT_0 * \ln(L_{j0}^{NKIS}/L_{j0})$
% Other non classified activities	$LO_{j0} = \ln(L_{j0}^{Other}/L_{j0})$	WT* (% Other non classified activities)	$WT_0 * RS_{j0} = WT_0 * \ln(L_{j0}^{Other}/L_{j0})$

$L$  = employment;  $i$  = industry;  $j$  = city;  $F$  = number of firms;  $A_m$  = number of years required to obtain an educative level  $m$ ;  $\alpha$  = average of population above 25 years old with an educative level  $m$ ;  $WS$ = intra-industry network matrix (synergy);  $WT$ = inter-industry network matrix (complementarity).

<sup>(1)</sup> Education weights ( $A_m$ ): Individuals can read and write but with difficulty = 2.5; Primary education or equivalent = 5; Lower secondary education = 8; Upper secondary and Post-secondary 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;

<sup>(2)</sup> 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 the municipality can have (minimum = 0; maximum = 7).

Two strategies are used to control network effects. The first is the inclusion of certain connectivity indexes (Capello 2000; Trullén and Boix 2001). These indexes were constructed using the number of network connexions for 1991 as an indegree or

outdegree indicator<sup>14</sup>. 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 indexes: indegree synergy, indegree complementarity, outdegree synergy, outdegree complementarity. The indegree index takes into 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 the initial year. 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 ( $WT$ ) for the initial year. The network matrices were row-standardized so that the network coefficients can be interpreted as direct elasticities.

#### 4.3. Econometric estimation

Three main models arise: 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 are row-standardized, the coefficients can be interpreted as direct elasticities.

Linear non-spatial model:

$$Y = \beta_1 SDIM_{ij_0} + \beta_2 SP_{ij_0} + \beta_3 EXP_{ij_0} + \beta_4 DIV_{ij_0} + \beta_5 P_{j_0} + \beta_6 INC_{j_0} + \beta_7 AEDU_{j_0} + \beta_8 Inf_{j_0} + \beta_9 OInf_{j_0} + \beta_{10} LHT_{j_0} + \beta_{11} LMHT_{j_0} + \beta_{12} LMLT_{j_0} + \beta_{13} LLT_{j_0} + \beta_{14} LKS_{j_0} + \beta_{15} LNKS_{j_0} + \beta_{16} RS_{j_0} + e \quad (19)$$

Linear non-spatial model with degree index for network effects:

$$Y_{ij_0} = \text{Linear non-spatial model} + \beta_{17} IS_{ij_0} + \beta_{18} IC_{ij_0} + \beta_{19} OS_{ij_0} + \beta_{20} OC_{ij_0} + e \quad (20)$$

Cross-regressive spatial model:

$$Y_{ij_0} = \text{Linear non-spatial model} + \beta_{21} WS \cdot SP_{ij_0} + \beta_{22} WS \cdot EXP_{ij_0} + \beta_{23} WT \cdot DIV_{ij_0} + \beta_{24} WT \cdot P_{j_0} + \beta_{25} WT \cdot INC_{j_0} + \beta_{26} WT \cdot AEDU_{j_0} + \beta_{27} WT \cdot OInf_{j_0} + \beta_{28} WT \cdot LHT_{j_0} + \beta_{29} WT \cdot LMHT_{j_0} + \beta_{30} WT \cdot LMLT_{j_0} + \beta_{31} WT \cdot LLT_{j_0} + \beta_{32} WT \cdot LKS_{j_0} + \beta_{33} WT \cdot LNKS_{j_0} + \beta_{34} WT \cdot RS_{j_0} + e \quad (21)$$

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<sup>14</sup> The indegree (outdegree) is the number of inward (outward) directed graph links from a given graph vertex in a directed graph.

Since these models do not incorporate any temporal or spatial lagged variable, they can be estimated by OLS. However, initial OLS estimations reveal 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 to 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 by changing the prior<sup>15</sup>. Additionally, extremely collinear variables were removed. 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 groups. All estimations include 267 municipalities, except the high-technology manufactures sector, where only 65 municipalities have initial and final employment. In order to perform a control of any selection bias, we use Heckman's two-stage process (1979)<sup>16</sup>. Finally, several spatial tests were calculated for the estimated models by testing the possibility of lag or error specifications.

#### 4.4. Results

The three models show an acceptable fit with an adjusted  $R^2$  between 0.34 and 0.63, in a similar range to Glaeser et al. (1992) and Henderson et al. (1994). It tends to be slightly better for high and medium-high knowledge manufactures and services (0.41 to 0.63 as opposed to 0.34 to 0.41). The fit also tends to be slightly better for the spatial models. Regarding the most parsimonious model, the Akaike statistic fluctuates between the non-spatial and the subcentre specification while the Schwarz statistic prefers the cross regressive (network) model in six of seven cases. An additional approximation to the Bayes factor confirms a preference for the cross-regressive model, even though it is weak.

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<sup>15</sup> 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 to control the convergence of the model (LeSage 1999, p.124-134).

<sup>16</sup> 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 on the other variables was observed. Since this ratio resulted to be non-significant, we offer the estimations without it.

Consistent with these results, agglomeration variables suffer little variations in their coefficients and statistical tests when subcentre or network variables are added. In fact, the subcentres do not reveal any remarkable behaviour with respect to the other municipalities. These results also hold when the centrality coefficients are substituted by dummies emphasizing the main subcentres. Other usual variables such the price of land as a proxy of urbanization diseconomies or local patents as a proxy of innovative activity were tested without producing statistically significant coefficients. Non-linearities were also tested in all models and as opposed to De Lucio et al. (2002), no statistically significant coefficient was obtained.

The results show evidence of agglomeration and network economies and diseconomies. Statistically significant agglomeration economies show elasticities between -1.87 and 2.47 (between -0.70 and 0.59 excluding the HTM group). Statistically significant network economies show elasticities between -6.43 and 2.85 (between -0.86 and 0.40 excluding the HTM group).

1. Regarding the results of the cross regressive model (table 4), High-technology manufactures (HTM) reveals positive and statistically significant coefficients related to a small firm size ( $\beta = 1.16$ ), the number of export firms ( $\beta = 1.51$ ), road and other infrastructures ( $\beta = 3.10$  and  $0.61$ ), initial specialization in MLT industries ( $\beta = 0.45$ ), and a network effect related to diversity ( $\gamma = 2.55$ )<sup>17</sup>. They reveal negative and statistically significant coefficients associated with city size ( $\beta = -0.73$ ), higher education averages ( $\beta = -3.31$ ), higher income levels in the network ( $\gamma = -6.43$ ), initial specialization in MLT industries in the network ( $\gamma = -1.67$ ) and KIS in the network ( $\gamma = -2.15$ ). This leads to a profile of the municipalities where there is growth in these activities: they have a dynamic environment (small and export firms), good infrastructures (especially road infrastructures), a base of MLT industries, and they are connected with a diversified network environment. On the other hand, they are not very large and do not have high average education levels either.

2. Medium-high technology manufactures (MHTM) show positive and statistically significant coefficients related to a higher number of export firms in the municipality ( $\beta = 0.42$ ) and the network of cities ( $\gamma = 0.23$ ), diversity ( $\beta = 0.43$ ), initial specialization in MLTM industries ( $\beta = 0.27$ ), and KIS in the network ( $\gamma = 0.40$ ). They reveal negative and statistically significant coefficients associated with higher levels of

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<sup>17</sup> This effect is only significant at 10%.

initial specialization in the municipality ( $\beta = -0.68$ ) and the network ( $\gamma = -0.27$ ), population ( $\beta = -0.30$ ), road and other infrastructures ( $\beta = -0.27$  and  $-0.11$ ), and KnIS in the network ( $\gamma = -0.86$ ). Regarding the profile of the municipality where these activities reveal differential growth, these have export firms of these activities within the municipality and the network environment, a diversified structure with a base of MLT industries. On the other hand, these are medium and small municipalities, where the supply of infrastructures is not very good, and which avoid network links with the nodes specialized in upper functions (KIS).

3. Medium-low technology manufactures (MLTM) reveals positive and statistically significant coefficients related to a higher number of export firms in the municipality ( $\beta = 0.39$ ) and the network of cities ( $\gamma = 0.14$ ), and input-output effects related to initial specialization in MHTM ( $\beta = 0.20$ ), LTM ( $\beta = 0.35$ ) and KnIS ( $\beta = 0.22$ ). The negative coefficient of the small firm dimension can be interpreted as a differential positive growth related to firm dimension and not to a marshallian environment. They have negative and statistically significant coefficients associated with higher levels of initial specialization ( $\beta = -0.60$ ), population ( $\beta = -0.27$ ) and other infrastructures ( $\beta = -0.08$ ). The municipalities where these activities have a differential growth are medium and small size municipalities, with a local and network export-oriented environment and a higher firm dimension, and an important base in other manufacturing technology intensities.

4. Low technology manufactures (LTM) reveals positive and statistically significant coefficients related to a higher number of export firms ( $\beta = 0.18$ ), diversity ( $\beta = 0.43$ ), input output effects related to MHTM ( $\beta = 0.06$ ), MLTM ( $\beta = 0.07$ ) and the residual sector ( $\beta = 0.14$ ), and a network effect related to the dimension of the network neighbourhood ( $\gamma = 0.09$ ). They reveal negative and statistically significant coefficients associated with higher levels of initial specialization ( $\beta = -0.53$ ), population ( $\beta = -0.28$ ) education ( $\beta = -0.37$ ), and some network expulsion effects related to the initial specialization in MHTM ( $\gamma = -0.18$ ), KIS ( $\gamma = -0.10$ ) and KnIS ( $\gamma = -0.42$ ). This technology intensity grows in a profile of municipality with export firms, a diversified productive structure, with an initial base of MHTM, MLTM and RS activities, and

connected to the regional markets, but avoiding the network proximity to municipalities specialized in MHTM and services (KIS and KnIS)<sup>18</sup>.

5. Knowledge intensive services (KIS) reveal positive and statistically significant coefficients related to population ( $\beta = 0.19$ ), income ( $\beta = 0.59$ ) and education ( $\beta = 0.36$ ). Notice that diversity is positive ( $\beta = 0.14$ ) but only significant to 15%. KIS reveals negative and statistically significant coefficients associated with higher levels of initial specialization ( $\beta = -0.62$ ) and network competition and expulsion effects related to HTM ( $\gamma = -0.03$ ), MHTM ( $\gamma = -0.12$ ), LTM ( $\gamma = -0.34$ ) and RS ( $\gamma = -0.28$ ). Thus, KIS reveals a positive differential growth associated with typical environments of large cities (size, income and human capital) connected with a network of other cities not specialized in manufacturing.

6. Knowledge non-intensive services (KnIS) reveal positive and statistically significant coefficients related to a small firm size ( $\beta = 0.12$ ), diversity ( $\beta = 0.15$ ), income ( $\beta = 0.30$ ), road infrastructures ( $\beta = 0.14$ ) and HTM in the network of cities ( $\gamma = 0.02$ ). They reveal negative and statistically significant coefficients associated with higher levels of initial specialization ( $\beta = -0.51$ ), population ( $\beta = -0.09$ ) and network competition and expulsion effects related to the existence of export firms in these activities ( $\gamma = -0.02$ ), LTM ( $\gamma = -0.11$ ) and KIS ( $\gamma = -0.08$ ). This indicates that higher growth rates lead to a profile of high-income residential municipalities (first and second residence) and tourist municipalities (medium and small municipalities, with high levels of income and good road infrastructures).

7. The Residual sector (RS) reveals positive and statistically significant coefficients related to a small firm size ( $\beta = 0.23$ ), road infrastructures ( $\beta = 0.20$ ) and export firms in the other municipalities of the network ( $\beta = 0.05$ ). They reveal negative and statistically significant coefficients associated with higher levels of initial specialization ( $\beta = -0.41$ ), education ( $\beta = -0.23$ ), HTM ( $\beta = -0.01$ ), MLTM in the network ( $\beta = -0.10$ ) and LTM in the municipality ( $\beta = -0.09$ ) and the network ( $\beta = -0.14$ ). The heterogeneity of the group and the sign and significance of the coefficients do not suggest any evident municipal profile.

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<sup>18</sup> Since the spatial tests (LM-Lag 4.98 > LM-error 2.78) suggest the existence of an additional spatial lag in the dependent variable for LTM group, a heteroskedastic bayesian regressive-regressive model was estimated for this sector. The autoregressive parameter  $\rho=0.1635$  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 weak evidence of a lag in the dependent variable for Medium-low technology industries, but in this case the estimated parameter  $\rho$  was not significant.

Table 4. Cross-regressive spatial model. Bayesian Heteroskedastic Linear Model Gibbs Estimates

Dependent variable: Ln Employment growth rate							
	HTM	MHTM	MLTM	LTM	KIS	KnIS	RS
Ln Small firm size	<b>1.1608</b> *** (0.0001)	-0.0578 (0.3096)	<b>-0.1851</b> * (0.0681)	0.0031 (0.4848)	0.0609 (0.2547)	<b>0.1297</b> ** (0.0373)	<b>0.2327</b> *** (0.0000)
Ln Specialization	0.0134 (0.4753)	<b>-0.6873</b> *** (0.0000)	<b>-0.6000</b> *** (0.0000)	<b>-0.5310</b> *** (0.0000)	<b>-0.6281</b> *** (0.0000)	<b>-0.5165</b> *** (0.0000)	<b>-0.4109</b> *** (0.0000)
Ln Export firms	<b>1.5111</b> *** (0.0000)	<b>0.4204</b> *** (0.0001)	<b>0.3942</b> *** (0.0000)	<b>0.1845</b> *** (0.0001)	-0.1301 (0.1135)	0.0378 (0.1468)	0.0032 (0.4885)
Ln Diversity	0.3665 (0.2955)	<b>0.4342</b> *** (0.0066)	0.1515 (0.1568)	<b>0.4356</b> *** (0.0000)	0.1469 (0.1424)	<b>0.1545</b> *** (0.0046)	0.0828 (0.1138)
Ln Population	<b>-0.7325</b> *** (0.0003)	<b>-0.3061</b> *** (0.0004)	<b>-0.2741</b> *** (0.0001)	<b>-0.2842</b> *** (0.0000)	<b>0.1973</b> *** (0.0008)	<b>-0.0980</b> *** (0.0022)	-0.0298 (0.1918)
Ln Income	1.7871 (0.1823)	0.0904 (0.4226)	-0.4943 (0.1098)	0.0045 (0.4936)	<b>0.5993</b> ** (0.0228)	<b>0.3033</b> ** (0.0234)	-0.0822 (0.3508)
Ln Road infrastructures	<b>3.1042</b> *** (0.0002)	<b>-0.2748</b> * (0.0944)	0.1419 (0.2461)	-0.0011 (0.495)	0.1119 (0.2276)	<b>0.1483</b> ** (0.0351)	<b>0.2032</b> ** (0.0184)
Ln Other infrastructures	<b>0.6199</b> * (0.0808)	<b>-0.1134</b> ** (0.0375)	<b>-0.0848</b> * (0.0598)	0.0148 (0.3122)	0.0535 (0.1309)	0.0230 (0.1248)	-0.0178 (0.2858)
Ln Education	<b>-3.3139</b> ** (0.0111)	0.0363 (0.4466)	-0.2383 (0.1835)	<b>-0.3767</b> *** (0.0083)	<b>0.3620</b> ** (0.0330)	0.0189 (0.4234)	<b>-0.2388</b> ** (0.0262)
Ln Rate of self-employment	<b>-1.3076</b> * (0.0566)	<b>-0.2613</b> * (0.0701)	-0.0752 (0.3440)	<b>-0.2741</b> *** (0.0032)	-0.0589 (0.3144)	<b>-0.1371</b> ** (0.0435)	-0.1051 (0.1027)
Ln % HTM	-	-0.0151 (0.1970)	-0.0092 (0.2994)	0.0014 (0.4414)	-0.0035 (0.3836)	0.0024 (0.3464)	<b>-0.0171</b> ** (0.0125)
Ln % MHTM	0.0265 (0.4663)	-	<b>0.2083</b> *** (0.0001)	<b>0.0697</b> ** (0.0102)	0.0341 (0.2095)	0.0088 (0.334)	-0.0126 (0.2982)
Ln % MLTM	<b>0.4552</b> * (0.0607)	<b>0.2790</b> *** (0.0000)	-	<b>0.0733</b> ** (0.0207)	-0.0042 (0.4689)	-0.0184 (0.2242)	-0.0092 (0.3739)
Ln % LTM	-0.0822 (0.4275)	-0.0296 (0.3680)	<b>0.3501</b> *** (0.0002)	-	0.0812 (0.1262)	-0.0091 (0.3877)	<b>-0.0930</b> *** (0.0099)
Ln % KIS	0.2600 (0.1434)	-0.0647 (0.1586)	-0.0200 (0.3854)	-0.0063 (0.4306)	-	0.0011 (0.482)	-0.0292 (0.1610)
Ln % KnIS	-0.8484 (0.1881)	-0.1778 (0.1370)	<b>0.2246</b> * (0.0790)	0.0170 (0.4169)	0.1668 (0.1244)	-	0.0182 (0.4096)
Ln % RS	-0.1035 (0.4099)	0.0531 (0.3228)	0.0963 (0.1852)	<b>0.1426</b> ** (0.0166)	0.1023 (0.1064)	0.0477 (0.1313)	-
WS* Ln Specialization	-	<b>-0.2798</b> * (0.0833)	-0.0082 (0.4878)	0.0693 (0.2692)	-0.0419 (0.3392)	0.0692 (0.2376)	0.0880 (0.2245)
WS * Ln Export firms	-	<b>0.2323</b> ** (0.0158)	<b>0.1432</b> * (0.0682)	0.0200 (0.3252)	0.0174 (0.3690)	<b>-0.0293</b> * (0.0580)	<b>0.0503</b> * (0.0752)
WT* Ln Diversity	<b>2.8593</b> * (0.0917)	0.3177 (0.1898)	-0.1874 (0.2685)	-0.0916 (0.3079)	0.2266 (0.2014)	-0.0928 (0.1630)	-0.0739 (0.2859)
WT* Ln Population	0.3690 (0.1499)	-0.0773 (0.1540)	0.0515 (0.2406)	<b>0.0922</b> ** (0.0264)	0.0708 (0.1037)	0.0311 (0.1661)	-0.0004 (0.4970)
WT* Ln Income	<b>-6.4343</b> * (0.0591)	-0.8833 (0.1456)	0.7845 (0.1575)	-0.0845 (0.4311)	<b>-0.7455</b> * (0.0991)	0.2108 (0.2248)	0.4100 (0.1211)
WT* Ln Other infrastructures	-0.0809 (0.4499)	0.0212 (0.4396)	0.0084 (0.4772)	0.0587 (0.2382)	-0.0587 (0.2737)	0.0386 (0.2400)	0.0433 (0.2536)
WT* Ln % HTM	-	-0.0112 (0.3597)	0.0297 (0.1734)	0.0066 (0.3601)	<b>-0.0385</b> ** (0.0461)	<b>0.0214</b> ** (0.0377)	-0.0016 (0.4553)
WT* Ln % MHTM	0.4386 (0.2929)	-	0.0632 (0.2826)	<b>-0.1856</b> *** (0.0006)	<b>-0.1286</b> * (0.0656)	0.0117 (0.3888)	0.0114 (0.3992)
WT* Ln % MLTM	<b>-1.6767</b> ** (0.0417)	-0.0968 (0.2574)	-	-0.0549 (0.2297)	-0.0455 (0.3149)	-0.0040 (0.4648)	<b>-0.1071</b> ** (0.0321)
WT* Ln % LTM	-0.9998	0.0171	0.0285	-	<b>-0.3455</b> ***	<b>-0.1148</b> **	<b>-0.1483</b> **

	(0.1088)	(0.4631)	(0.4387)		(0.0082)	(0.0329)	(0.0245)
WT* Ln % KIS	<b>-2.1521 **</b>	<b>0.4013 ***</b>	-0.0143	<b>-0.1006 *</b>	-	<b>-0.0856 *</b>	-0.0050
	(0.0133)	(0.0010)	(0.4593)	(0.0947)		(0.0534)	(0.4690)
WT* Ln % KnIS	-2.9914	<b>-0.8680 **</b>	-0.4762	<b>-0.4227 **</b>	-0.3400	-	-0.1881
	(0.1605)	(0.0156)	(0.1037)	(0.0132)	(0.1431)		(0.1384)
WT* Ln % RS	1.2174	-0.0911	<b>0.3093 *</b>	-0.1586	<b>-0.2861 **</b>	0.0885	-
	(0.1772)	(0.3411)	(0.0906)	(0.1131)	(0.0341)	(0.1419)	
R <sup>2</sup>	0.7786	0.4927	0.4137	0.4674	0.5065	0.4451	0.4252
R <sup>2</sup> -adj	0.6367	0.4354	0.3475	0.4072	0.4507	0.3824	0.3603
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
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
Obs	65	267	267	267	267	267	267

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

HTM = High Tech. Manufactures; MHTM = Medium-High Tech. Manufactures; MLTM = Medium-Low Tech. Manufactures; LTM = Low Tech. Manufactures; KIS = Knowledge Intensive Services; KnIS = Knowledge non-Intensive Services; RS = Other.

#### 4.5. Limitations of the measurement

The empirical application presents some limitations that should be taken into account in later research. 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. Second, even though sectoral commuting data provides a feasible measure for network relationships, other data such as industry inter-firm calls or commercial transactions would provide a more exact design of the network. Third, employment data offers a partial view of the stock and variation of knowledge in cities. Data for added value by knowledge industry, R+D, etc. should complete the analysis. Fourth, many of these data are preferable on an establishment level in order to avoid the hypothesis used to aggregate on a city level and to allow an individualized treatment of the inter-firm spillovers. Fifth, the labour demand model does not capture labour savings coming from the capital or 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 capture life-cycle effects.



## **5. Conclusions and implications for policy-making**

The objective of this paper was to measure the impact of different kinds of knowledge and external economies on urban growth in an intraregional context. The main hypothesis is that knowledge leads to growth, and that this knowledge is related to the presence of agglomeration and network externalities in cities. We develop a three-stage methodology: first, we measure the amount and growth of knowledge in cities using the OCDE (2003) classification and employment data; second, we identify the spatial structure of the area of analysis (networks of cities); third, 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 are easily applicable to a large number of regions.

We apply this methodology to a case study: Catalonia. Regarding employment growth, the results show the existence of two simultaneous structural processes: a change from manufacturing to services, and a change towards more knowledge-intensive activities. The main amount of knowledge intensive employment (manufacturing and services) is concentrated in the metropolitan region of Barcelona.

Regarding the network of cities, the main structure of the network reveals 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 around the Catalanian territory. The differentiation between high and low-knowledge network links takes on 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 have a positive growth differential associated with a small firm size, export firms and infrastructures. Medium-high technology industries have a positive differential related to 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 have a positive differential growth related to export firms, diversity, other local specialization and network size. Knowledge-intensive services relate their positive differential growth to urban size, the average income and the education level of the residents. Knowledge non-intensive services have a positive growth differential associated with diversity, average income, road infrastructures and specialization in high-tech industries in the network. Diseconomies tend to be associated with specialization (life-cycle effect), urban size (except for Knowledge-intensive services) and spatial competition between industries.

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 they suggest the more appropriate environments and factors to develop each type of knowledge, as well as where and why, will tend to locate a particular firm or industry depending on its knowledge intensity and specialization.

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