Investment decision and the spatial dimension: Evidence from firm level data*

Luisito Bertinelli
(bertinelli@core.ucl.ac.be)
(Aspirant FNRS – CORE and IRES, Université catholique de Louvain)

Rosella Nicolini
(rnicolini@pareto.uab.es)
(CODE, Universitat Autonoma de Barcelona - IRES, Université catholique de Louvain)

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ABSTRACT

This paper proposes to investigate the effect of spillovers on location decision of firms. We develop an analysis merging the geographer toolbox with the standard econometric techniques. For a chosen sample of sectors, through the spatial data analysis, we test the existence of positive spatial autocorrelation for R&D investments that lead R&D expenditure to cluster. Moreover, we succeed in detecting in how far the local environment may influence the firm decisions in R&D investments. Data confirm that the proximity to other firms investing in R&D may produce positive externalities. Finally, the diversity vs. specialization debate is tackled.

Keywords: Local clustering, R&D investment, and spatial autocorrelation.
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1. Introduction

Different theories of agglomerations have been proposed. Most of them principally enlighten the importance of macroeconomic features that drive the location choices of firms (see Fujita *et al.* 1999). Hence, they tend to neglect that the sources of agglomeration may also stem from the direct interaction among firms themselves that belong to a specific location. This feature has however been taken into account by another approach that deserves more attention to the micro-foundations of the spatial agglomeration (see Saxenian, 1994 for a case study approach).

In the latter approach, accounting for space becomes a crucial component, as sources of agglomeration are built around the presence of positive externalities such as *local spillovers.*

The issue of detecting and measuring spillovers has a longstanding tradition in economics. Ever since Marshall's industrial districts, all kinds of spillovers/externalities have been postulated. The main characteristic attributed to *spillovers* is their diffusion throughout *different* means than the simple exchange via the *market* mechanisms, hence making their detection cumbersome.

In this paper, our aim is to provide a contribution able to find the possible interrelation between the spreading of spillovers and the spatial dimension, so as to lead firm to select some preferred areas where to locate. According to the database we dispose, for a sample of Belgian firms, we will concentrate on the analysis of the strategic choice of location of firms, related to their decision to invest in R&D in their sector of production.

More specifically we aim at: (i) analyzing the spatial distribution of innovative activity across Belgian districts by determining the varying propensities to cluster across several sectors and (ii) determining the spatial extend of agglomeration economies, and their impact on R&D investment.

Departing from the hypothesis of an aspatial economy, we suppose that knowledge embodied in R&D activities is subject to distance decay effects, making spillovers localized.

Compared to other studies in innovation economics (for instance Audretsch, 1998), our approach pays more attention to the geographic element in drawing the existence of clusters of firms investing in R&D. In order to do so, we dispose of a database made up by more than 1600 plants, thus allowing us to refine the location of the firm to a smaller dimension than the regional one. In the first part of this paper, data will be aggregated at the district level. There are 43 administrative districts in Belgium, displaying an average land area about 700skm.[1] However, working on such small areas, whose borders are administratively set, may produce some bias in the study as the economic interaction among firms may be cross-bordering. Acknowledging for this spatial unit issue, we have recourse to the geographers toolbox in order to see whether the district dimension fits as a measure of R&D externalities. In other words, we evaluate if districts are somehow self-contained in terms of R&D. This outcome will allow us to choose more properly the extent to which knowledge may flow across space.

In the second part, we turn our attention towards the way R&D proximity favors R&D investment intensity. We choose to concentrate on the *dichotomy specialization versus diversity*. To our knowledge, our approach basically differs from other studies in this field by building the analysis on *density* variables. Indeed as pointed out by Ciccone and Hall (1996), there exists a direct linkage between *density* and *proximity*: higher density of economic activity will enhance productivity. Nevertheless, very few studies have paid attention for density as an explicit element of the theory. Rearranging the assumption of these authors to

[1] To make a useful comparison, a Belgian average district size is about a quarter of the smallest US state, Rhode Island (about 2700skm) and slightly smaller than New York city (about 800skm).

our framework, we attempt to determine whether the spatial density of R&D investment is really able to affect the R&D effort of each firm taken individually.

Our results support the idea that clustering of innovation activity sustains R&D investment. We are able to depict that some districts are more specialized,[2] whereas others tend to have a broader economic activity. As a corollary, we are able to detect sectors, which display a stronger sensitiveness to urbanization economies, whereas localization economies will be more favorable to others.[3]

1.1 Related literature

The analysis of the investment decision in R&D has been tackled from different points of view in industrial economics. Basically, two strands can be isolated. The former investigates the trade off between the equilibrium and the optimum level of investment in R&D under imperfect information and technological spillovers (Tirole chapter 10, 1988), while the latter focuses on the determinants of R&D investments, as well as the consequences related to the technological transfers that may occur between local and multinational firms. This second approach has been largely followed in studies that involve the analysis of small open economies with a large presence of multinational subsidiaries (as, for instance, in Cincera, 2000 or Cassiman and Veugelers, 1999b for the Belgian case).

A less widespread stream of literature has tried to examine the rationale of the spatial distribution of R&D activity. It is widely recognized that proximity matters for making information circulate. As argued by Arrow (1962) tacit knowledge in non-rival nature can easily spill over and it can be exploited in various economic applications. Hence, being close to an external source of information increases the impact of spillovers from that source.

In the early 1990's, Glaeser *et al*. (1992) and Henderson *et al.* (1995) made an important contribution to this literature by extending the debate on localization versus urbanization to a dynamic framework. Namely, localization economies are the result of economic interactions within a given sector, while urbanization economies are fostered by the economic interactions across sectors. As a consequence of that, according to the first authors, diversity favors spillovers, whereas the second authors argued that concentration of an industry within a city promotes knowledge spillovers and facilitates innovative activity.

Audretsch and Feldman (1996) and Feldman and Audretsch (1999) rise a similar questioning in the specific case of innovation activities rather than the broader view of all production activities. The empirical evidence proposed in the first study suggests that industries, in which knowledge-inputs play a central role, tend to cluster for exploiting the benefits issuing from the tacit knowledge flows.[4] Moreover, they set out that spatial clusters mainly result from the rise of new economic knowledge rather than solely from the concentration of production. In their second contribution, these authors explicitly tackle the problem of diversity *vis-à-vis* of specialization and highlight that, as in Jacobs (1969), science-based diversity is more conducive of knowledge spillovers, rather than diversity per se. Identifying the three sources of economic knowledge with R&D, skilled labor and size of the pool of basic science, these authors conclude that the location of production is expected to be more concentrated in those industries where knowledge spillovers are relevant, i.e. R&D intensive industries.

Various components that may spur the knowledge spillovers have been detected. Audretsch (1998) argues that this role may be played by local institutions (e.g. universities,

[2] By *specilization* we means the propensity of a district to display high rate of R&D investment only in one or a few sectors.
[3] These outcomes are consistent with Capron and Cincera (1999).
[4] This argument takes its roots in a basic idea presented by Marshall (1890), taken over later by Krugman (1991), according to which information flows and knowledge spillovers may be sensitive to geographic obstacles.

trade associations, local business organizations etc.) providing technical and financial services that (i) firms cannot afford individually and (ii) make them collaborate. This decentralized and fluid environment also promotes the diffusion of intangible technological capabilities. As a consequence, according to Love and Roper (2001), in Germany as well as in UK (although with a weaker evidence at hand), plants located in regions displaying a higher level of innovation (on average) tend to be more innovation-intensive. This is also the case for the innovative industrial districts (above all in the Third Italy), ICT clusters (Silicon Valley, Route 128-Boston), or local technological incubators (industrial poles built around universities or research centers).

However, data limitations often prevent from exploring this kind of issues within smaller geographic units than nations or regions and to get more details about the intensity of spillovers effects. As argued by Wallsten (2001), we know that firms tend to cluster in certain regions so as to benefit from knowledge spillovers. Nevertheless, the possible relationship between the distance among firms and the strength of spillovers remains to be explored. Indeed firms may benefit from common labor and input markets by co-locating in the same area, while the role of the geographical distance for knowledge spillovers is less clear. While information may flow through mechanisms such as Internet or scientific journals, knowledge flow mechanisms may be more closely linked to geography.

1.2 Basic issues

The general problem tackled throughout this paper is visually synthesized in Figure1 where we have plotted the density function of aggregate R&D density across Belgian districts. It is straightforward to observe that firms investing in R&D are not uniformly spread across space. They polarize around a few locations, highlighting a high density of R&D, while most other districts have low ones, hence suggesting that the geographic distribution of R&D activity is far from being random.

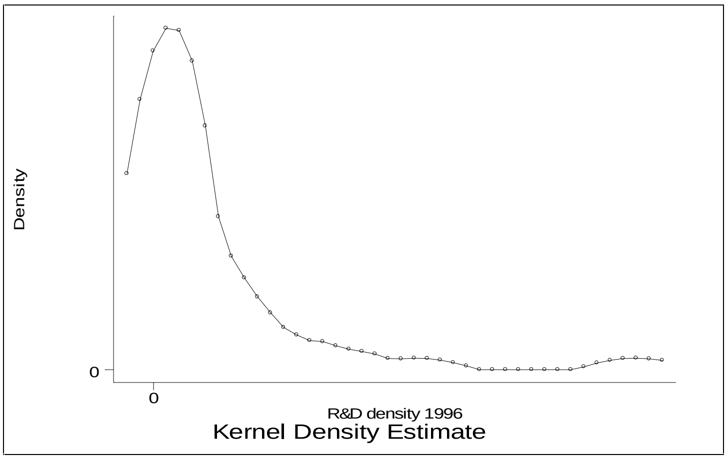

Fig. 1: Kernel distribution of R&D density in Belgium in 1996.
(Estimation by Gaussian Kernel)

The five most intensive districts in R&D represent about 15% of total Belgian land area but 68% of total Belgian R&D. This skewed distribution does however not tell us whether high density R&D districts tend to be close to one another. This issue is closely linked to the areal unit problem as we will see in Sections 2 and 3.

A supplementary question that is taken up is directly related to the decision of individual firms to invest in R&D, according to their location in high respectively low density districts.

Hence, the first part of the paper is going to deal with the issue of the relevant spatial unit, whereas part 2 copes with the latter mentioned issues of agglomeration economies.

The remainder of the paper is structured as follows. In Section 2 we present an outline of the tools applied in order to detect the presence of spatial autocorrelation among Belgian districts (a more formal presentation is provided in Appendix A). Section 3 turns to give a review of data we used as well as the indices of global and local spatial autocorrelation. In Section 4, firm level econometric specifications are run, aiming at detecting the impact of agglomeration economies on R&D investment decisions. Finally, Section 5 concludes.

2. Exploratory Spatial Data Analysis: aims and tools

The techniques that are applied in the first part of the analysis are resumed by Anselin (1995) as follows:

Exploratory Spatial Data Analysis is a set of techniques aimed at describing and visualizing spatial distributions, identifying atypical localization or spatial outliers, detecting patterns of spatial association, clusters or hot spots, and suggesting spatial regimes or other forms of spatial heterogeneity. Central to this conceptualization is the notion of spatial autocorrelation or spatial association, i.e., the phenomenon where locational similarity (observations in spatial proximity) is matched by value similarity (attribute correlation).

This means that observations are not independent statistically. Clusters of events, people, facilities are referred to as positive spatial autocorrelation, whereas negative spatial autocorrelation refers to arrangements where people, events or facilities are dispersed. Rather than being an exception, spatial dependence is a rule when working with social and economic phenomena (Varga, 1998).

Two sources of spatial autocorrelation are usually distinguished:

- The first and most obvious reasons are misspecification of the model or measurement errors e.g. omitted autocorrelated variables, differing geographical scale at which data may be collected and by which the process of interest may operate. This last problem is very common, as political and/or administrative boundaries do not necessarily reflect economic reality.
- A further and more interesting reason for the economics profession is spillover effects between geographical units. Distance is not neutral. The intensity of interactions among spatial units is in this case determined by their proximity.

From a statistical point of view, spatial autocorrelation implies that a sample contains less information than a sample of uncorrelated observations. For instance, the use of correlation coefficients or OLS regressions assumes that the observations have been selected randomly. If the observations, however, are spatially clustered in some way, the estimates obtained may be inefficient or even biased, because the areas with higher concentration of events will have a greater impact on the model estimate. Moreover they will overestimate precision, since for events tending to be concentrated, there are actually fewer number of independent observations than are being assumed (Levine, 1999).

Beyond the technical point of view, the existence of spatial dependence conveys information about the distribution of social or economic activities that should not be neglected when trying to model or forecast some phenomena. If economic or social activity is not randomly distributed, one should account for this a priori supplementary information.

In view of this, ESDA represents a set of techniques, that allows one to detect different types of spatial dependence.

2.1 Spatial connection

In order to take account of spatial dependence, a link between every pair of spatial units has to be defined, leading to a spatial weight matrix W of dimension (N, N), where N stands for the number of observations. Different types of matrices can be used. A first possibility is to consider contiguity matrices, where the elements of the matrix W are given by

$$
\begin{aligned}
w_{ij} &= 1 \text{ if spatial units } i \text{ and } j \text{ are neighbors, with } i \neq j \text{ where } i,j=1\ldots N \\
&= 0 \text{ otherwise.}
\end{aligned}
$$

This definition refers to first order contiguity and $w_{ij}=1$ implies that region i and region j share common borders. Beside first-order contiguity matrices, k^{th} order contiguity can be defined by means of algorithms (Anselin - Smirnov, 1996).

In the contiguity specification, only adjacent areas are supposed to be related. Conversely, when using distance based weighting matrices, one can account for the influence of areas farther away, i.e. areas that have no common borders. In this case, the elements of the weighting matrix are given by:

$$
\begin{aligned}
w_{ij} &= 1/d_{ij}^{\alpha} \quad \text{if } d_{ij} < \bar{d} \\
&= 0 \quad \text{otherwise}
\end{aligned}
$$

where d_{ij} is the distance between region i and region j, $\bar{d}$ introduces a threshold value to the spread of spatial dependence, and α varies inversely to the importance given to remote observations. This weighting matrix is more general in the sense that it allows for gradual relations between spatial units, rather than binary relations as supposed by contiguity matrices.

Finally, more stylized weighting matrices can be used, reflecting for instance the volume of trade between any pair of regions, the number of commuters, or any other relevant relation between pairs of regions, depending on what one aims to study. However these weights have always to be defined exogeneously, which may be problematic when using economically based weights. The relevance of the definition of the weighting matrix will appear in the following subsection.

2.2 Global Spatial Autocorrelation

There are a number of formal statistics that attempt to measure spatial autocorrelation. Among those, Moran's I statistic (Moran, 1950) and Geary's C (Geary, 1954) statistic are probably the most popular ones. They are very similar indices and are often used in conjunction, although the Moran statistic is slightly more robust. In what follows, we will concentrate on the Moran's I.[5] This statistic compares the value of a continuous variable at any location with the value of the same variable at surrounding locations. Formally, it is defined as:

$$
I = \tfrac{N}{S} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad \text{with } S = \sum_i \sum_j w_{ij}\,, \quad \bar{x} = \frac{\sum_i x_i}{N} \qquad \text{and } i \neq j
$$

[5] See Appendix A for further details.

where x_i represents the value of the observation in region i, N is the total number of observations (Belgian districts in our case), $\bar{x}$ is the mean of the variable across all observations and w_{ij} is the weight as defined above. Values of I significantly higher than the expectation of Moran's statistic will denote positive spatial autocorrelation. In other words, similar values, either high values or low values, are more spatially clustered than could be caused purely by chance. The converse being true for values of I significantly lower than the expectation of I.

2.3 Local Spatial Autocorrelation

Moran's I is a global statistic in the sense that only spatial autocorrelation of all the observations are accounted for, but it does not enable us to appreciate the contribution of every single observation. On the contrary, local measures of spatial autocorrelation are supposed to account for this drawback, by appreciating whether there are local spatial clusters of high or low values and detect atypical localization.

There are basically two (complementary) methods at hand to account for local spatial autocorrelation: Moran Scatterplots (Anselin, 1996) and Local Indicators of Spatial Association (LISA) (Anselin, 1995).

2.3.1 The Moran Scatterplot

The Moran Scatterplot is a visual device rather than a statistic. It gives an intuition whether each spatial unit is similar (or dissimilar) to its neighbors, but it does not give any indication on the statistical significance of local spatial clustering as LISA does.

Drawing a Moran Scatterplot basically consists in plotting the standardized values of a certain variable x with its spatial lag Wx, with W defined as above. In this plot, observations along the upward sloping diagonal will be associated with positive spatial autocorrelation, whereas observations along the main diagonal highlight negative spatial autocorrelation. Whether we have association of high-high (HH), high-low (HL), respectively low-low (LL), low-high (LH) values depends on whether we are above or below average.

As Moran's I is formally equivalent to the slope coefficient of a regression of Wx on x, this provides insights into the extent to which individual pairs (x_i, Wx_i) influence the global measure, exert leverage or may be interpreted as outliers. In order to isolate different outliers, influence measures can be used, as for instance Cook's distance, which measures the extent to which the regression coefficient would be changed by eliminating the particular observation (Le Gallo and Ertur, 2000).

2.3.2 Local Indicators of Spatial Association (LISA)

Anselin (1995) has defined the basic concept of a LISA as any statistic that satisfies two requirements[6]:

- The LISA for each observation indicates the extent to which there is significant spatial clustering of similar values around that observation,
- The sum of the LISAs for all observations is proportional to the global indicator of spatial association.

In other words, LISA is an indicator of the extent to which the value of an observation is similar or different from its neighboring observations.

[6] Further discussions about the two following points are given in Appendix A.

Anselin (1995) applies the concept to a number of spatial autocorrelation statistics. The most commonly used being the Local Moran statistic I_i (the use of Moran's I statistic as a LISA). The definition of I_i is:

$$I_i = \frac{(x_i - \bar{x})}{m} \sum_j w_{ij} \left(x_j - \bar{x} \right) \qquad \text{with } m = \frac{\sum (x_i - \bar{x})^2}{N}$$

Positive values of I_i indicate the clustering of similar values (high-high or low-low), whereas negative values indicate clustering of dissimilar values (high-low or low-high). Inference is based on pseudo-significance levels, hence standard threshold rejection criteria are corrected by the number of observations (Anselin, 1995).[7]

Finally, the local Moran statistic is a good indicator of either "*hot spots*" or "*cold spots*", that is, spatial units that are different from their neighborhood. *Hot spots* would be seen where the number of events in a region is much higher than in nearby regions, whereas *cold spots* are related to a region where the number of events is much lower than in nearby regions. To see whether a region is a hot spot or a cold spot, one has to look at the absolute value of the events in the region, hence the complementarities between Moran Scatterplots and LISAs.

3. **Data and spatial indicators**

Our data set consists of a panel of 1637 Belgian firms, spreading 48 2 and 3-digit NACE-BEL sectors, of which we will retain about half in this section. This represents a random, but stratified[8] sample of the total Belgian enterprises. This sample has been selected among all the firms that participated to the inquiry on R&D investment in Belgium in 1998. It includes all firms that declared to invest permanently or regularly in R&D and it accounts among others for their R&D expenditures in 1996 and 1997.

The R&D variable accounted for all the funds invested directly by firms, be it for own projects, or co-operation projects. In general, firms succeed in financing their R&D activity either via their own cash flows or requesting financial support to regions at particular advantageous conditions.[9]

All firms included in our database are classified by sectors, according to the NACE-BEL classification (2 or 3 digits). Nevertheless, not all sectors contain a sufficient number of observations to allow running estimations. Consequently, we carry out a preliminary selection of our data to keep in our sample only sectors with a sufficiently large number of firms involved permanently in R&D activities. Sectors in our database contain about 60-65 observations. Accordingly we selected a list of 21 sectors (see Table 1). As it can be easily checked, our sample displays a variety of sectors and it does not focus only on sectors expected to be R&D intensive. This allows us to carry out tests whose results can be compared following the intensity of R&D for different sectors.

In what follows, results for global and local Moran indices are provided, our purpose being to test if similar values for the observations of labor and R&D investments tend to cluster across space.[10]

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[7] See Appendix A for further details.

[8] This sample has been collected by the Belgian SSTC (*Services fédéraux des affaires scientifiques, techniques et culturelles*) for the R&D survey 1998. We engaged in preserve their confidentiality at firm level.

[9] Generally, regional authorities grant loans to local firms according to a grid of conditions these firms have to satisfy. In particular they have to prove that projects they intend to finance are expected to carry out benefits not only to them but also to the whole economy of the region they belong to. Additional information may be found at the following web-sites: http://www.iwt.be for Flemish region, and http://mrw.wallonie.be/dgtre/ for Walloon region.

[10] Moran statistics were carried out with *SpaceStat 1.90* software package (Anselin 1999).

3.1 The MORAN index

Belgium is divided into 589 townships (*communes*) and 43 districts (*arrondissements*). In order to avoid too many zero entries in our data set, we decided to work with district level data, eliminating however the district of Brussels. Due to its status of capital city of Belgium, and its relative small size, it constitutes an outlier in our statistics, shadowing all other results. As alluded above, two types of spatial connection matrices were computed: two distance based matrices, and a first-order contiguity matrix. Indeed, changing the functional form of distance in the weights allows us to focus on different features.

We run twelve different specifications: row standardized and raw matrices, with three types of weights (*1/d*, *1/d²* and *contiguity*), and each of these specifications is run once including Brussels, and then excluding it.[11]

Row-standardization is implemented as follows $\tilde{w}_{ij} = \frac{w_{ij}}{\sum_j w_{ij}}$ and $\sum_j \tilde{w}_{ij} = 1$, where $\tilde{w}_{ij}$ is the row-standardized weight. In this case, weights take values between 0 and 1 and they can be compared across models. However, row-standardization has a major drawback: it introduces arbitrary asymmetries between pairs of regions.

In order to avoid statistical bias connected with size effect, we deal with density variables. Nevertheless, as our variables are taken in density, including Brussels in our estimations tends to obscure any other result, due to Brussels' special status as a district, and due to its small size. This is most striking when dealing with local indicators.

In Table 1, results are based on row standardized weighting matrices, excluding Brussels.[12] Spatial autocorrelation for R&D expenditures for 1996 and 1997, and the sectoral labor force for 1996 and 1997 has been tested. Only statistically significant results are reported in the table. Inference is based on the permutation approach (see Appendix A).

Results of Table 1 confirm that spatial autocorrelation seems to be the rule rather than the exception in the case of Belgian firms investing in R&D. Out of 21 sectors, 10 highlight a positive spatial correlation for employment, supporting that the assumption of random distribution is not sustainable. However we cannot infer that the remaining 11 sectors are randomly distributed across space, but they *are* with respect to our choice of spatial unit, significance criterion and data availability.

By contrast, R&D is positively autocorrelated across districts only in one sector. To clarify this somewhat paradoxical result there are two explanations at hand. From a statistical point of view, it is important to note that our database contains less information about R&D than labor. These missing values could affect the degree of significance of the results. Moreover, another reason could come from the choice of the spatial unit of reference (i.e. Belgian districts have an average area of 709 square km). This selection is arbitrary, and relies solely on our data availability.

[11] According to Anselin (1995) row standardization prevents us from bias related to the scale effects.
[12] Further results are reported either in Appendix B or are available upon request.

Table 1: ***Moran's I statistics***

Density variables - Brussels excluded;
Distance-based (*1/d*), row-standardized weighting matrix; years 1996-97

2-digits		Labor	R&D
15	Manufacture of foodstuffs, alcohol and tobacco		
17	Production of textiles, clothing, leathers and shoes		
22	Paper and paper board industry, publishing and printing house		
24	Chemical industry		
25	Manufacturing of rubber and plastic products		
26	Production of other non-metallic mineral products		
28	Metallurgy and manufacture of metal products		
29	Manufacture of machines and equipment tools		
31	Manufacture of electrical and electronic equipment and instruments		
32	Manufacture of radio, TV and communication tools		
33	Manufacture of clocks, medical care tools and other precision instruments		
34	Manufacture of means of transport		
45	Constructions		
50	Commerce of means of transport		
70	Real estate industry		
72	Computer and data processing industry		
73	Research and Development (service)		
75	Public Administration and Social services		
3-digits			
244	Pharmaceutical industry		
271	Iron industry		
722	Software industry		

Legend: 1% 5% 10%

If we assume that Belgian districts are more or less self-contained from the point of view of research, it is possible that R&D investments would highlight spatial autocorrelation only for a finer spatial scale, so that it cannot be detected in the present study. In other words, this would imply that R&D activity might be subject to more localized spillovers than production activities. Section 3.2 explores this path.

Moreover, our result support the idea that traditional manufacturing sectors, such as textile, publishing and printing display important spatial autocorrelation of innovating firms. The same happens for sectors belonging to the service category (excluding the public administration) or for high technological sectors, such as computer and data processing industry or software industry. By contrast, for sectors that exploit technologies at medium R&D intensity, the location of activities is hardly spatially correlated. Special attention should be paid to the case of *Means of transports*. In Belgium, as stressed by various studies (for instance Cassiman & Veugelers (1999a, 1999b)) this sector is mainly composed of an important number of multinational subsidiaries assembling final products. Those subsidiaries (that invest in R&D according the strategic plans of their headquarters) do not display a strong positive spatial autocorrelation. On the contrary, the sector that is in charge of the *Commerce of the means of transports* shows a higher degree of spatial autocorrelation (although not significant at the 5% confidence level).

Further results with different weighting matrices tend to support the outcomes previously discussed (see Appendix B, Table 7). In most cases, the statistical significance of indices we previously detected is reinforced, assessing for the non-randomness of the distribution of spatial activity.

3.2 Local clustering indicators

In this section, we deepened the autocorrelation analysis developed above by depicting the existence of local spatial clusters of activities. As described in Section 2.3, we use two complementary tools at hand: Moran Scatterplots and LISAs. The first allows us to determine whether, for a given sector, a district is positively or negatively spatially autocorrelated. We are in presence of positive spatial autocorrelation (*high-high*[HH]; *low-low*[LL]) whenever high (low) values of the selected variables in district *i*, correspond to high (low) values of the same variables in the surrounding districts *j*. In the same way, negative spatial autocorrelation (*high-low* [HL]; *low-high* [LH]) is present when high (low) values of the selected variables in a district *i* are associated with low (high) values of the same variables in the surrounding districts *j*. The Moran Scatterplots for density of R&D and Labor 1997 are plotted in Appendix C. As standardized values are used, one can easily detect outliers by the 2-sigma rule.[13]

However, as noted above, no inference can be drawn upon Moran Scatterplot. Conversely, LISA provides statistics but they leave open the question, whether we are facing positive (HH or LL) respectively negative (HL or LH) autocorrelation. Hence, combining results of Moran Scatterplots and LISAs allows us to circumvent the respective drawbacks of each of these tools.

In Table 2, we have inserted the results for Labor and R&D, with a distance based ($w_{ij}=1/d_{ij}$) weighting matrix. As for Table 1, Brussels is excluded from the sample, in order to prevent it from obscuring all other results due to the excessive weight taken by the Belgian capital city in terms of production and innovation activity.[14] Table 2 should be interpreted as follows: columns represent sectors, and rows, districts. Each resulting cell has been divided into two parts. The left part informs about Labor, whereas the right is devoted to R&D. Whenever a cell is black, we are in an HH configuration (positive autocorrelation); gray colored cells, on the other hand, represent HL configuration (negative autocorrelation). There is only one gray cell that represents an LH spatial autocorrelation: *Commerce of means of transport* in Dendermonde (Flanders). The results displayed in Table 2 deserve a twofold interpretation.

At first glance, one realizes the uneven distribution of the statistically significant results between Belgian regions[15] (Labor as well as R&D, HH or HL): Flanders encompasses overall 77% of them. This finding can immediately be related to the density of employment and R&D activity of the two Belgian regions. Indeed, on average, concentration of the production activity is more than twice as dense in Flemish districts as in Walloon ones. For R&D, this ratio increases even to more than 2.5. The origin of this discrepancy cannot be put on the account of a regional imbalance bias of our data sample, since 50% of our data relates to Walloon firms. Moreover, as Flemish districts are only on average about 25% smaller than Walloon, a first conclusion that can be drawn is that Flanders has a denser employment and innovation basis, leading to more statistically significant results.

Furthermore, beside its denser production and R&D activity, Flanders has also a broader sectoral coverage. Except for sector 33 (*Manufacture of clocks, medical care tools and other*

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[13] Values of Cook's distance were not reported but are available upon request.

[14] Results for contiguity matrix and distance based matrix $w_{ij}=1/d_{ij}^2$ are reported in Appendix B, whereas results including Brussels are available upon request. As for Table 1, results presented in Table 2 were obtained by merging the results of years 1996 and 1997, and only common results for these two years were retained.

[15] The upper part of the table (districts 11 to 46, except 25, plus 71-73) refers to Flemish locations, the rest being in Wallonia (districts 51-93, except 71-73, plus 25).

precision instruments), all other sectors appear at least once as High[16] (HH or HL) on the Flemish side in our result table, when considering Labor and R&D. By contrast, in Wallonia, more than half of the sectors never appear with statistically significant High (HH or HL) level of either production or R&D. Consequently, adding this result to the evidence that more then 60% of Flemish districts highlight a HH configuration, (in contrast with 20% of Wallonia), one may conclude that R&D activity is denser in Flanders than in Wallonia, where R&D adopts of spot pattern.

Looking now at the issue of specialization versus diversity, one immediately realizes that Walloon districts are mostly specialized in very few sectors[17]: Charleroi in *Manufacture of electronic and electrical equipment*, Soignies in *Manufacture of precision instruments*, Waremme in *Manufacture of means of transport* and Liège in *Iron industry*. Conversely, Flemish districts are much more diversified. Very few districts are specialized just in one activity. Moreover, there is no significant sector override between Walloon and Flemish regions. Hence this reflects two very different paths of development: small scale, diversified investments in Flanders; large scale, concentrated (sectorally as well as spatially) investments in Wallonia.

In our local statistics, HH configurations tend to dominate HL ones. This is consistent with the results given in Table 1, where only significant positive spatial autocorrelation had been detected. Indeed, excluding sector 271, all the darkened cells in Table 1 can be recovered with black cells in Table 2. Interestingly, for R&D, about 75% of results fit in the case of category HL, meaning that activity is strongly clustered within the district. Conversely, only 37% of the results for employment do highlight an HL configuration, meaning that production activity is spread across district borders. In an agglomeration economy perspective, this could mean that externalities are much more localized in R&D activity, rather than production activity. Put differently, there are stronger *distance decay effects* in the former than in the latter. This may depend on the kind of externalities at work: knowledge spillovers for R&D or labor pooling for production activity.

Concerning the externalities issue, our results provide some hints to the localization versus urbanization economies debate. Looking at the R&D side, all but two districts (Antwerpen, as well as Halle-Vilvoorde) highlight a very specialized pattern, with at most one R&D cluster per district. In contrast, production activity seems to be much more prone to cross-fertilization, when looking at the number of districts having a High (either HH or HL) level of at least two sectors. Nonetheless, our results do not allow us to determine clearly the sector mix that would emerge. In the following section, we will provide some more insights into this issue by analyzing the case of 4 sectors, trying to detect, whether localization or urbanization economies dominate.

Comparing results of Table 2 to Tables 8 and 9 in Appendix C, a few remarks may be drawn. First, taking the square inverse distance-weighting matrix, respectively the contiguity matrix is not neutral. In the former case, less weight is given to remote observations, whereas in the latter case, only direct neighbors are considered to be worth taking into account, avoiding any problem on the functional form of the distance intervention. Second, results of the inverse distance-weighting matrix do coincide in 71% of the cases with those of the square inverse distance-weighting matrix, and to 51% with the contiguity based weighting matrix. Although results seem to differ quite significantly, when the weighting matrices change, the qualitative results listed above tend to remain the same throughout these different types of matrices. Hence, although details of our results change considerably, the main conclusions still hold.

[16] That is, higher than average, according to our definition of Moran Scatterplot.
[17] In the present context, by *specialization* we mean districts that do highlight High (HH or HL) levels of labor respectively R&D for only one or very few sectors.

Summarizing our findings, we may conclude that

- Spatial autocorrelation is largely dominant: R&D is not distributed randomly across locations. Moreover, districts seem to be an adequateunit of measure for R&D spillovers, as negative spatial autocorrelation is dominant for the R&D density variables, thus supporting the idea of self containment of districts in terms of R&D.
- Global positive spatial autocorrelation is the result of positive and negative local autocorrelation. Labor, and hence production activity tend to be in an HH configuration, while R&D is mostly in an HL configuration, thus leading to the conclusion that higher concentration of R&D activity may be due to more localized spillovers.
- The degree of specialization respectively diversity tends to vary among districts, depending upon others in which sector they are active. Overall, Flemish districts are significantly more diversified than Walloon ones.
- Excluding Brussels from our sample, 2 poles (in Flanders) seem to emerge from the 42 remaining districts: Antwerpen and Mechelen.

Table 2: Local statistics

Density variables; Brussels excluded;
Weights: 1/d; pseudo-significance levels: 5%; years 1996-97.

	NACE code	15	17	22	24	25	26	28	29	31	32	33	34	45	50	70	72	73	75	244	271	722
District code	**Labor R&D**	Manufacture of foodstuffs, alcohol and tobacco	Production of textiles, clothing, leathers and shoes	Paper and paper board industry, publishing and printing house	Chemical industry	Manufacturing of rubber and plastic products	Production of other non-metallic mineral products	Metallurgy and manufacture of metal products	Manufacture of machines and equipment tools	Manufacture of electrical and electronic equipment and instruments	Manufacture of radio, TV and communication tools	Manufacture of clocks, medical care tools and other precision instruments	Manufacture of means of transport	Constructions	Commerce of means of transport	Real estate industry	Computer and data processing industry	Research and Development (service)	Public Administration and Social services	Pharmaceutical industry	Iron industry	Software industry
11	Antwerpen																					
12	Mechelen																					
13	Turnhout																					
23	Halle-Vilvoorde																					
24	Leuven																					
25	Nivelles																					
31	Brugge																					
32	Diksmuide																					
33	Ieper																					
34	Kortrijk																					
35	Oostende																					
36	Roeselare																					
37	Tielt																					
38	Veurne																					
41	Aalst																					
42	Dendermonde																					
43	Eeklo																					
44	Gent																					
45	Oudenaarde																					
46	Sint-Niklaas																					
51	Ath																					
52	Charleroi																					
53	Mons																					
54	Mouscron																					
55	Soignies																					
56	Thuin																					
57	Tournai																					
61	Huy																					
62	Liège																					
63	Verviers																					
64	Waremme																					
71	Hasselt																					
72	Maaseik																					
73	Tongeren																					
81	Arlon																					
82	Bastogne																					
83	Marché en Famenne																					
84	Neufchateau																					
85	Virton																					
91	Dinant																					
92	Namur																					
93	Philippeville																					

Legend : *high-low* *low-high* *high-high*

4. Clustering and externalities

The main results of the previous section confirm that the role of the spatial proximity is not negligible when one intends to highlight how the surrounding environment affects a single firm decision. Firms close to other firms that invest in R&D are more likely to invest in R&D rather than more remote firms. Moreover, clustering allows firms to exploit positive externalities.

In order to assess for the interpretation of local clustering as an indirect measure of externalities between firms, we ran an empirical investigation. Before turning to the practical application, we provide a theoretical framework. In the spirit of this analysis, our purpose is to show that the effort in R&D activities by a single firm stems both from the internal resources or strategies, but it is also linked to the local environment that firms belong to.

As we discussed in the introduction, one of the advantages that firms can exploit by clustering is the reciprocal exploitation of the spillovers related to their activity. Spillovers reinforce the increasing returns to scale that a firm can take advantage from when locating in an agglomeration. As far as there does not exist a single way to model externalities, we concentrate on two alternative methods each corresponding to a different theoretical background. Then, examining the findings of the econometrics applications, we should be able to draw conclusions upon which framework may be more appropriate.

4.1 Spillovers as means to reduce fixed costs

In the first model, we basically assume that the main agglomeration force stems from the increasing returns to scale related to the production function. In other terms, poles of agglomeration allow firms to exploit external increasing returns to scale in R&D activity. In this case, externalities are simply included in the production function itself and they are evaluated as means to reduce production costs.

To figure out theoretically this kind of approach, we refer to the technology function used in standard economic geography models (see, for instance, Fujita *et alii.* 1999):

$$L_i = \beta_i + \gamma Y_i \,. \tag{1}$$

where each firm i needs labor, L_i, as an input, proportionally to the level of final output (Y_i) according to a marginal costs coefficient γ (>0), and to some fixed costs (β_i). The higher the level of production, the lower will be the impact of fixed costs.

In this model, we establish that fixed costs are mainly related to R&D expenditures. We assume that belonging to a cluster of firms investing in R&D means allowing a firm to reduce its own investment in R&D ($R\&D_i$) because of the existing externalities it can exploit. Put differently, these externalities reduce the level of fixed costs borne by firms.

To that extent, we posit that the externalities on R&D expenditures for a firm i connected with the R&D activity of all the remaining (n-1) firms are proportional (according to the parameter $\delta > 0$) to the amount of money invested by each remaining firm. For sake of simplicity we assume that all of them invest (on average) the same amount ($\overline{R\&D}$). So far, the level of fixed costs may be represented by the following equation:

$$\beta_i = R\,\&\,D_i - \delta(\overline{R\,\&\,D})(n-1)\,. \tag{2}$$

Replacing equation (2) in (1) and rearranging all the terms, we obtain the following expression:

$$R\,\&\,D_i = L_i - \gamma Y_i + \delta(\overline{R\,\&\,D})(n-1) \tag{3}$$

The first two terms on the right hand side are a proxy of the amount of capital available to be invested in R&D, while the last one accounts for the role of externalities. In order to disentangle between localization and urbanization economies, equation (2) is refined hereafter. Still keeping all other hypothesis unchanged, we introduce two different types of externalities that a firm *i* may exploit. The former concerns the positive spillovers a firm captures from the other firms belonging to the same sector in the same spatial unit (here districts), while the latter accounts for the possible externalities generated by the proximity of all other firms belonging to the same spatial unit, but to any other sector. For sake of simplicity, we assume that the average level of R&D investment is the same for all the firms. In addition, we represent the saving amounts (in terms of fixed costs) generated by the spillovers (in the case of firms belonging to the same district) as $\delta_1(n_i-1)(\overline{R\,\&\,D})$, i.e. a proportion δ_1 of the whole amount invested by firms belonging to this district. Symmetrically, the spillovers generated by all the other firms may be quantified as $\delta_2(n-\ n_i-1)(\overline{R\,\&\,D})$, i.e. a proportion δ_2 of the amount of R&D expenditure of all the other firms that do not belong to that sector, but to the same district. Under these assumptions, equation (2) becomes:

$$\beta_{i\in j} = R\,\&\,D_{i\in j} - [\delta_1(n_1-1)I_{i\in j} + \delta_2(n-n_1-1)I_{i\notin j}](\overline{R\,\&\,D})\,. \tag{4}$$

where *i* refers to the firm, and *j* to the sector.

By replacing equation (4) in equation (2) we get the following expression:

$$R\,\&\,D_i = L_i - \gamma Y_i + [\delta_1(n_1-1)I_{i\in j} + \delta_2(n-n_1-1)I_{i\notin j}](\overline{R\,\&\,D})\,, \tag{5}$$

which is analogous to equation (2), but accounts for the two possible sources of spillovers

As stated above, we are interested in detecting the conditions that could give particular incentives to firms to devote more capital than their competitors to R&D. To this end, we develop a discrete choice model by exploiting the findings we get in the previous section. In particular, we want to evaluate whether just belonging to a HL spatial unit can be really an important feature to distinguish the behavior of the firms in R&D matters. In other words, assessing whether simple close proximity to other firms investing in R&D is a crucial discriminating factor in R&D investing decisions.

In order to capture this kind of effect we will deal with a discrete choice version of equation (5), since the lack of information prevents us from estimating directly that expression. Indeed, we built a dependent variable (RDCA)[18] such that:

RDCA = 1 if the R&D expenditure of a firm i is larger than the average of the R&D expenditure of all other firms of the same sectors
0 otherwise.

We elaborate this variable for all the sectors and for the two years (1996 and 1997) included in our database. As stated in equation (5), the central feature is to distinguish whether localization or urbanization economies prevail. To do so, two variables, derived from ESDA results, were tested: BHL and AHL. In addition to these agglomeration economy proxies, we include a certain number of control variables: BXL, LCA, LLABOR (see Box 1 for the definition of these variables). Whereas the first control shall account for the special status of the Brussels districts, the two last are intended to neutralize size effects.

[18] Estimations taking RDCA as a dependent variable but replacing average by median and third quartile where also run but led to qualitatively the same results.

Equation (5) finally provides the following specification:

$$\Pr\{RDCA=1\}=\phi\{\beta_0+\beta_1 Dummy97+\beta_2 BXL+\beta_3 BHL+\beta_4 AHL+\beta_5 LCA+\beta_6 LLabor\}.$$

Box 1

Dummy 97	Dummy variable for year 1997
Dummy BXL	Dummy variable for a firm belonging to Brussels arrondissement
Dummy BHL	Dummy variable for a firm belonging to a HL spatial unit for the sector of the firm we account for
Dummy AHL	Dummy variable for a firm belonging to any HL spatial unit for aggregate R&D
LCA	Logarithm of total sales per firm
LLABOR	Logarithm of total labor per firm

As mentioned above, we apply a discrete choice method of analysis. In particular we deal with a LOGIT model by applying the STATA 6.0 software package. Table 3 displays the results.

Table 3: Econometric results

Dependent variable: **RDCA**
Method of estimation: LOGIT
Value in brackets: Standard Error

	(1)	(2)	(3)
Constant	-0.915*** (0.097)	-0.859*** (0.101)	4.095*** (0.875)
Dummy97	0.2105 (0.139)	0.212 (0.139)	0.157 (0.144)
Dummy BXL	-0.175 (0.261)	-0.232 (0.262)	-0.172 (0.268)
Dummy BHL	0.173 (0.231)	0.204 (0.233)	0.141 (0.239)
Dummy AHL		-0.433** (0.217)	-0.526** (0.224)
LCA			-0.453*** (0.097)
LLABOR			0.244** (0.109)
Log Likelihood	-609.18	-607.08	-581.17
Pseudo R-square	0.003	0.006	0.05
Obs.	993	993	993

*** 1% significance level; ** 5%; * 10%

These results are somewhat disappointing. There are only a few variables that affect in a significant manner the probability of the firms to invest more than average amounts of money in R&D. Turning to specification (3), the two last control variables (LCA and LLABOR) do not impact on the significance of the coefficient of agglomeration economies (i.e. localization economies do remain insignificant, whereas urbanization economies are significant). Hence, the simple condition to be located in a HL spatial unit, which displays a specialization in investing in R&D in its own sector, is not sufficient to spur firms to invest larger capital in R&D than the average. Moreover, the presence of other firms (in the same spatial unit) investing in R&D in other sectors behaves as a disincentive for the firms we take into account.

This first set of estimations suggests that an econometric estimation based on a model of economic geography does not lead to consistent results. Thinking of spillover effects just as a way to reduce production costs seems to be inconvenient and this involves the need to refine the terms of our econometric approach. Moreover, assuming that localization respectively urbanization economies may act differently according to the industry, sector specific aspects should also be taken into account.

4.2 The spillovers effects and the R&D intensity-density trade off

In this second model we explicitly examine the idea whether the *spatial density* of firms investing in R&D is a force driving the amount of R&D expenditures of firms. In our setting, focusing on density implies accounting for distance decay effects in the diffusion of spillovers. As has been presented by previous theoretical as well as empirical findings, this effect is as stronger as the firms are abundant and workers mobile. Indeed a firm may benefit from the R&D managed by other competitors not only by direct exchange of R&D information, but also by the personal contacts employees may have. So far, a higher density of workers means that it is more likely for a worker to get in touch with the others and make information circulate easily. As a consequence of that, it is also reasonable to think of the frequency of the contacts among workers as an alternative way to foster spillovers circulation as well as a way to reduce the amount of resources devoted to R&D activity.

The approach we propose hereafter grants a lot to Ciccone and Hall (1996) and Ciccone (2001).

Basically, we posit the assumption that the externality depends multiplicatively on a particular measure of density. However, we qualify this assertion by assuming that *spatial density* has to be interpreted as a measure of externalities. A standard functional form that fits to this proposal is the Cobb-Douglas. As in the foregoing, R&D expenditure and labor are the only production input. We get the following equation:

$$Y_i = A_i (L_i)^{\alpha} \quad with\ A_i = \left(R\&D_i\right)(E_i)^{\beta}, \quad \alpha, \beta > 0, \tag{6}$$

where (Y_i) is the level of final output for a firm i, L_i, the demand of labor and A_i corresponds to the R&D component that can be split in two parts. Indeed, the R&D as an input involves both the direct expenditure of the firms itself in R&D ($R\&D_i$) and the spillovers benefits it gets from surrounding firms (E_i) (that will be described in detail below).

Replacing the terms in the previous equation we get:

$$Y_i = \left(R\&D_i\right)(E_i)^{\beta}(L_i)^{\alpha}.$$

Rearranging the terms of equation (6), we solve this expression for the per-firm investment in research and development. This indicator helps us in isolating the spillovers *(E_i)* effects.

The corresponding expression is given by [19]

$$\frac{R\&D_i}{Y_i} = E_i^{(-\beta)}\left(L_i\right)^{(-\alpha)}.$$

Once we assume the existence of the externalities, we define their main components too. For the reasons mentioned above, we mainly concentrate on two measures of density: the former embodies the R&D activity at firm level and the latter the mobility of workers (D_{La}). As in the previous case, we distinguish between spillovers connected with the R&D activity of firms in the same sector (D_{rda}), localization economies, and those of all firms in the same spatial area but in different sectors (D_{rds}), urbanization economies.

[19] The parameters α, β are constant. They embody the elasticity of each input with respect of the quota of R&D over sales.

Let us assume that externalities *(E_i)* are the result of an existing trade-off between those densities. To fit the previous equation to our assumptions, we need to define *(E_i)* in the following way:

$$E_i = \frac{D_{La}}{D_{rds} D_{rda}}, \tag{7}$$

Replacing (6) in (7) and rearranging the terms

$$\frac{R\&D_i}{Y_i} = \left(\frac{D_{rds} D_{rda}}{D_{La}} \right)^{\beta} (L_i)^{-\alpha},$$

and by taking logarithms, the previous expression becomes:

$$\log\left(\frac{R\&D_i}{Y_i} \right) = \beta\left[\log(D_{rds}) + \log(D_{rda})\right] - \beta \log(D_{La}) - \alpha \log(L_i). \tag{8}$$

In our empirical test we concentrate on equation (8). For our purpose we aim at disentangling the effect that each kind of density may have on the R&D effort (intended as R&D intensity) at firm level. We propose a double range of estimations. In principle, we look at how our sample of firms (taken as a whole) behaves *vis-à–vis* the detected trade-off between density and intensity. To this end, we deal with panel data estimations. Once we detected the general trend of the sample, we concentrate on a selected number of sectors to isolate some details more related to each industry. Box 2 defines the variables we account for in our estimations.

Box 2

Dummy96	Dummy variable for year 1996
LD	In the pooled sample, logarithm of the density of R&D expenditure for all sectors except the sector we alternatively account for -by arrondissement-.
LD15	Logarithm of the density of R&D expenditure for all sectors except sector 15 by arrondissement
LD24	Logarithm of the density of R&D expenditure for all sectors except sector 24 by arrondissement
LD29	Logarithm of the density of R&D expenditure for all sectors except sector 29 by arrondissement
LD70	Logarithm of the density of R&D expenditure for all sectors except sector 70 by arrondissement
LDL	In the pooled sample, logarithm of the density of the labor force for sector we alternatively account for -by arrondissement -
LDL15	Logarithm of the density of the labor force for sector 15 by arrondissement
LDL24	Logarithm of the density of the labor force for sector 24 by arrondissement
LDL29	Logarithm of the density of the labor force for sector 29 by arrondissement
LDL70	Logarithm of the density of the labor force for sector 70 by arrondissement
LDRD	In the pooled sample, logarithm of the density of R&D expenditure for sector we alternatively account for - by arrondissement-
LDRD15	Logarithm of the density of R&D expenditure for sector 15 by arrondissement
LDRD24	Logarithm of the density of R&D expenditure for sector 24 by arrondissement
LDRD29	Logarithm of the density of R&D expenditure for sector 29 by arrondissement
LDRD70	Logarithm of the density of R&D expenditure for sector 70 by arrondissement
LLABOUR	Logarithm number of workers per firm
LRDCHAF	Logarithm of R&D expenditures over total sales per firm

In the first stage, we concentrate on the whole sample of firms in our database. The purpose of these estimations is to detect any possible relationship between R&D intensity at firm level (using as a proxy the ratio between the R&D expenditure and the total sales of each firm) and the three different measures of R&D densities.

According to equation (8), the two R&D densities (D_{rda} and D_{rds}) should exhibit a positive relationship with the R&D intensity. Indeed, they basically resume the positive effects that R&D spillovers of other firms exert directly on R&D effort of the firm we account for. On the contrary, for the reasons mentioned before, the labor density (D_{la}) is expected to be negatively related to the dependent variable. Indeed, supposing that externalities come from the concentration of R&D activity rather than from the general concentration of production activity, one may consider that labor concentration acts as a negative rather than a positive force. Hence, the labor variable is supposed to exhibit a negative coefficient. Relying on equation (6), for a given level of sales, a higher value of L_i (as input) involves devoting fewer resources to R&D.

Table 4: Econometric results: intensity versus density

Dependent variable: **LRDCHAF**
Method of estimation: Various
Value in brackets: Standard Error

	Pooled	**Pooled** Sectoral fixed effects[20]	**Within** Per firm fixed effects
Constant	-5.152*** (0.266)	-5.067*** (0.890)	-3.001*** (0.727)
Dummy96	-0.197** (0.084)	-0.147* (0.080)	-0.062* (0.034)
LLABOUR	-0.398*** (0.028)	-0.344*** (0.031)	-0.032*** (0.112)
LD	0.009 (0.023)	-0.027 (0.024)	0.009 (0.063)
LDL	-0.598*** (0.035)	-0.433*** (0.039)	0.318 (0.238)
LDRD	0.703*** (0.028)	0.539*** (0.034)	0.123*** (0.038)
Obs	983	983	983
Adjusted R-square	0.49	0.54	
R-square: Within			0.05

*** 1% significance level; ** 5%; * 10%

The previous table reports the results of the estimation of equation (8) for the whole sample. We applied a Panel data procedure with three different methods of estimation. For all the three methods the outcomes are quite homogeneous and consistent. Whenever the density variables are significant, they display the expected coefficient. In particular, *LDRD* is always positive and highly significant. This result confirms the role and the importance of positive spillovers for R&D investment inside each sector (localization economies). Moreover, it appears also that spillovers coming from the R&D activities in other sectors do not seem to play any role. Indeed, the corresponding variable (*LD*) is always negative or close to zero. To sum up, these results tend to support the importance of 'specialization' versus 'diversity'.

[20] The Fisher statistic for joint significance of the sector dummy rejects the null hypothesis.

Nonetheless, this last result needs some further qualifications. In particular, as noted in the previous subsection, estimations on the whole sample may hide differences across sectors. Put differently, we aim at investigating if there exist a few sectors for which the R&D effort in the other sectors plays any role in fostering the R&D investment in that particular sector. Given the sample of data at hand we concentrate on 4 particular sectors: Food and Beverage (15), Chemical (24), Manufacture of Machines and Equipment Tools (29) and Real Estate Industry (70). These sectors are quite heterogeneous and each of them covers a range of peculiar features.

We repeat the same exercise as before, adding the hypothesis of heterogeneity of firms for the estimations included in Table (6).

Table 5: Econometric results: intensity versus density

Dependent variable: **LRDCHAF**

Method of estimation: OLS with White methodology for correcting heteroskedasticity

Value in brackets: Standard Error

	Sector 15	**Sector 24**	**Sector 29**	**Sector 70**
Constant	-6.609*** (1.462)	-5.7*** (0.751)	-6.075*** (0.855)	-0.466 (0.390)
Dummy96	-0.013 (0.362)	-0.400 (0.256)	-0.192 (0.275)	-0.070 (0.068)
LLABOUR	0.048 (0.218)	-0.144 (0.100)	-0.052 (0.120)	-0.055*** (0.018)
LD15	0.020 (0.09)			
LD24		0.115* (0.062)		
LD29			0.02 (0.093)	
LD70				0.054* (0.032)
LDL15	-0.356** (0.178)			
LDL24		-0.264** (0.127)		
LDL29			-0.651*** (0.166)	
LDL70				-0.099** (0.051)
LDRD15	0.195 (0.157)			
LDRD24		0.324*** (0.115)		
LDRD29			0.507*** (0.119)	
LDRD70				0.087* (0.048)
Obs	70	81	72	76
Adjusted R-square	-0.02	0.12	0.18	0.08

*** 1% significance level; ** 5%; * 10%

Looking at the results displayed in the previous table, one immediately realizes that sensitiveness towards localization versus urbanization economies varies from sector to sector. Indeed the corresponding elasticities are positive and significant for the two types of agglomeration economies in case of sector 24 (*Chemical Industry*) and 70 (*Real Estate Industry*), supporting the idea that these sectors may benefit from intra- as well as inter-sectoral spillovers. Conversely, sector 29 (*Manufacture of Machines and Equipment Tools*) seems to be only subject to own sector spillovers and data for sector 15 (*Manufacture of foodstuffs, alcohol and tobacco*) point out no spillover sensitiveness at all.

Turning to Table 6, we included fixed effects in our estimations in order to take account of unobserved variables in the previous estimation.

Table 6: Econometric results: intensity versus density

Dependent variable: **LRDCHAF**
Method of estimation: Panel estimation with fixed effects per-firm
Value in brackets: Standard Error

	Sector 15	**Sector 24**	**Sector 29**	**Sector 70**
Constant	-4.200 (2.614)	1.793 (3.124)	-2.493 (5.025)	-1.344 (5.073)
Dummy96	-0.274*** (0.089)	-0.142 (0.088)	-0.112 (0.116)	-0.214 (0.251)
LLABOUR	-1.105*** (0.234)	-1.321** (0.624)	0.018 (0.858)	-0.901*** (0.243)
LD15	0.356 (0.349)			
LD24		-0.009 (0.110)		
LD29			-0.278 (0.501)	
LD70				0.067 (0.510)
LDL15	0.82 (0.722)			
LDL24		0.438 (0.495)		
LDL29			-0.515 (1.038)	
LDL70				0.068 (1.036)
LDRD15	0.327* (0.167)			
LDRD24		0.039 (0.061)		
LDRD29			0.135 (0.124)	
LDRD70				0.199 (0.439)
Obs	70	81	72	76
R-square Within	0.59	0.28	0.10	0.37

*** 1% significance level; ** 5%; * 10%

Working with fixed effect estimations, the significance of the coefficient of the variables mostly fails. Loss of significance may be due to the fact that our Panel only entails 2 periods. The only significant results concerns sector 15 (Food & Beverage), supporting the existence of localization economies, but not urbanization ones.

As a consequence of that, in the case we assume that firms are homogenous, sectorial estimations confirm that diversity and specialization are important in a few sectors (here, for instance, chemical and real estate), while for the mechanical one only specialization plays an important role. The same kind of result holds even for a traditional sector, such as food and beverage, when accounting for heterogeneity among firms.

5. Conclusions

In this study, we provide an empirical investigation on the spatial distribution of investments in R&D at firm level in the case of Belgium. For a sample of selected sectors, by computing Moran's *I* statistics we have detected positive spatial autocorrelation for most sectors. This result suggests that the distribution of R&D investment tends to be spatially dependent. As a consequence, innovation activity is not uniformly distributed across Belgium and several districts display a different technological specialization. The local spatial indicators reinforce this outcome. In the second part of the analysis, we concentrate more on the specialization-diversity trade-off. Dealing with an econometric investigation on a sample of chosen sectors, we find that the *specialization* component affects positively the R&D expenditures of firms, whenever the R&D contents are specific. By contrast, all sectors benefit positively from reciprocal spillovers, i.e. *diversity* seems to matter in R&D decisions.

In Belgium, as well as in other countries with important regional disparities, a spatial economic approach should help in drawing a map of the most performing or active firms (such as those who invest in R&D) to try to sketch some possible regional growth paths. One way to proceed should be to account for the existence of technological incubators (such as universities or other centers of research) as centripetal poles for innovating activity. More generally, it should also help to test more precisely how the local environment may affect the performance at firm level. Belonging to dynamic regions and locating in existing clusters of activities are expected to be important assets for firms, leading them to improve their economic performances.

6. References

L. Anselin (1995): 'Local Indicators of Spatial Association-LISA', *Geographical Analysis*, 27 (2), pp.93-115.

L. Anselin (1996): 'The Moran Scatterplot as an ESDA tool to assess local instability in spatial association', in: M. Fisher, H.J. Scholten and D. Unwin (Eds.) Spatial analytical perspectives on GIS. Taylor&Francis, London

__________ – O. Smirnov (1996): 'Efficient algorithms for constructing proper higher order spatial lag operators', *Journal of Regional Science,* Vol. 36, pp.67-89.

________ (1999): '*SpaceStat, a software package for the analysis of spatial data*', Version1.90, Ann Arbor, BioMedware.
__________ – O. Smirnov (1996): 'Efficient algorithms for constructing proper higher order spatial lag operators', *Journal of Regional Science,* Vol. 36, pp.67-89.

K. Arrow (1962): 'Economic welfare and the Allocation of Resources for Invention', in R. Nelson (ed.) : '*The Rate and Direction of Innovative Activity*', Princeton University Press.

D. B. Audretsch (1998): 'Agglomeration and the Location of Innovative Activity', *Oxford Review of Economic Policy*, Vol. 14, N°2, pp.18-29.

_____________- M.Feldman (1996): 'R&D Spillovers and the Geography of Innovation and Production', *American Economic Review*, vol.86(3), pp. 630-640.

H. Capron – M. Cincera (1999): '*The Flemish Innovation System: an external viewpoint*', VTO-Studies n.28.

B. Cassiman - R. Veuglers (1999a): '*R&D Cooperation and Spillovers : some Empirical Evidence*', CEPR discssion paper N°2330.

________________________(1999b): '*Importance of international linkages for local know-how flows. Some Econometric evidence from Belgium*', CEPR Discussion Paper n. 2337.

M. Cincera (2000*): 'Creative, transfer and absorptive capacities in Belgian manufacturing companies*', mimeo.

A. Ciccone (2001): "Agglomeration – Effects in Europe", *European Economic Review*, forthcoming

____________ - R. E. Hall (1996): "Productivity and the Density of Economic Activity", *American Economic Review*, vol.86(1), pp.54-70.

M. Feldman - D.B Audretsch (1999): 'Innovation in cities: Science-based diversity, specialization and localized competition', *European Economic Review*, vol. 43, pp. 409-429.

M. Fujita -P. Krugman - A. Venables (1999) : " The Spatial Economy", MIT Press

R.C. Geary (1954) : 'The contiguity ratio and statistical mapping', *The Incorporated Statistician*, 5, pp.115-145.

E.Glaeser – H. Kallal- J. Sheinkman- A. Shleifer (1992): 'Growth in Cities', *Journal of Political Economy*, vol. 100, pp. 1126-1152.

R. Henderson – A. B. Jaffe – M. Trajtenberg (1995) : '*Universities as a Source of Commercial Technology : a Detailed Analysis of University Patenting 1965-1988*', NBER Working paper N°5068.

J. Jacobs (1969): 'The Economy of Cities', Random House, New York.

P. Krugman (1991): '*Geography and Trade*', Cambridge, MIT Press.

_________-C. Ertur (2000): '*Exploratory Spatial Data Analysis of the distribution of the regional per capita GDP in Europe, 1980-1995*', Document de Travail LATEC, nº 2000-09, Université de Bourgogne, forthcoming in *Papers of Regional Science.*

N. Levine (1999): '*CrimeStat. A Spatial Statistics Program for the Analysis of Crime Incident Locations. User's Manual*', http://www.icpsr.umich.edu/NACJD/crimestat.html#SOFTWARE

J.Love - S. Roper (2000): "Location and network effect on innovation success:evidence for UK, German and Irish manufacturing plants", *Research Policy*, vol.30, pp. 643-661.

A. Marshall (1890): "Principles of Economics", London, MacMillan & C. (Edition 1920).

P. Moran (1950): 'A test for serial independence of residuals', *Biometrika*, Vol. 37, pp. 178-181.

A. Saxenian (1994) : '*Regional Advantage : Culture and Competition in Silicon Valley and Route 128*', Harvard University Press.

M. Tiefelsdorf - B. Boots (1995): "The exact distribution of Moran's *I*", Environment and Planning A, Vol. 27, pp. 985-999

J. Tirole (1988)**: '***The theory of industrial organization*', Cambridge, MIT Press.

A.Varga (1998): ' *University Research and Regional Innovation. A Spatial Econometric Analysis of Academic Technology Transfers*', Kluwer Academic Publishers.

S.J. Wallsten (2001): "An empirical test of geographic knowledge spillovers using geographic information systems and firm-level data", *Regional Science and Urban Economics*, vol.31, pp.571-599.

7. Appendix

- **Appendix A**

Moran's statistic

Moran's I is similar to a correlation coefficient in that it compares the sum of the cross-products of values at different locations, two at a time. However I is not restricted by the interval [-1,1]. The upper and lower limits of I depend on the eigenvalues of a matrix containing W.[21] When nearby points have similar values, the cross-product is high. Conversely, when nearby points have dissimilar values, the cross-product is low. More precisely, values of I significantly larger than the expected value of the Moran statistic, $E[I] = -\frac{1}{N-1}$, indicate positive spatial association, whereas significantly smaller values indicate negative spatial association. Inference can be based upon two approaches.

One can assume that the standardized variable $Z(I) = \frac{I - E[I]}{S_{E[I]}}$ has a sampling distribution, which follows a standard normal, that is with a mean of 0 and a variance of 1. A second interpretation is based on the permutation approach, where it is assumed that under the null hypothesis, each observed value could have occurred at all locations with equal likelihood. But instead of using the theoretical mean and standard deviation, a reference distribution is empirically generated for I, from which the mean and the standard deviation are computed. In practice, this is carried out by permuting the observed values over all locations and by re-computing I for each new sample. The mean and standard deviation for I are then the computed moments of the reference distribution for all permutations (Le Gallo- Ertur, 2000).

LISA

The local Moran's statistic I_i is given by:

$$I_i = \frac{(x_i - \bar{x})}{m} \sum_j w_{ij} (x_j - \bar{x}) \qquad \text{with } m = \frac{\sum (x_i - \bar{x})^2}{N}$$

It is straightforward to see that the sum of the local Moran's statistics can be written:

$$\sum_i I_i = \frac{1}{m} \sum_i \left[(x_i - \bar{x}) \sum_j w_{ij} (x_i - \bar{x}) \right]$$
$$= \frac{1}{m} \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})$$

while Moran's I is:

$$I = \frac{N}{S} \cdot \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$
$$= \frac{\sum_i I_i}{S \cdot \sum_i (x_i - \bar{x})/N} \qquad \text{with} \quad S = \sum_i \sum_j w_{ij}$$

Denoting $m = \sum_i z_i^2 / N$, the factor of proportionality between the sum of the local Moran's statistics and the global Moran is given by $\gamma = S \cdot m$, verifying hence Anselin's second condition.

Relating to Anselin's first condition mentioned in Section 2.3.2, an exact test of significance has not been worked out because the distribution of the statistic is not known. Therefore, an alternative approach is to base inference on the conditional randomization approach to yield pseudo significance levels (Anselin, 1995). The randomization is conditional in the sense that the value of x_i at location i is held constant and the remaining values are randomly permuted over the locations

[21] See Tiefelsdorf and Boots (1995) for further details.

in the data set. For each of these re-sampled data sets, the value of I_i can be recomputed. In the present study, inference was based on a 10000 permutations approach.

In particular, only $\sum_j w_{ij}(x_i - \bar{x})$ needs to be recomputed for each permutation as the term $\frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})/N}$ remains constant for a given region i.

A complicating factor in the assessment of significance of LISAs is that the statistics for individual locations will tend to be correlated. Due to this correlation, the usual interpretation of significance will be flawed. Consequently, in order to avoid distortions due to correlation, significance levels have to be approximated by Bonferroni inequalities or following the approach suggested by Sidák (Anselin, 1995). This means that in the case of N observations, if the overall significance is set to α, then the individual significance level α_i is set to α/N (*Bonferroni approach*) and $1-(1-\alpha)^{1/N}$ (*Sidák approach*).[22]

- **Appendix B**

Table 7: ***Moran's I statistics***

Density variables; Brussels excluded; Row-standardized weighting matrix

2-digits		$w_{ij}=1/d_{ij}^2$		*Contiguity*	
		Labor	R&D	Labor	R&D
15	Manufacture of foodstuffs, alcohol and tobacco				
17	Production of textiles, clothing, leathers and shoes				
22	Paper and paper board industry, publishing and printing house				
24	Chemical industry				
25	Manufacturing of rubber and plastic products				
26	Production of other non-metallic mineral products				
28	Metallurgy and manufacture of metal products				
29	Manufacture of machines and equipment tools				
31	Manufacture of electrical and electronic equipment and instruments				
32	Manufacture of radio, TV and communication tools				
33	Manufacture of clocks, medical care tools and other precision instruments				
34	Manufacture of means of transport				
45	Constructions				
50	Commerce of means of transport				
70	Real estate industry				
72	Computer and data processing industry				
73	Research and Development (service)				
75	Public Administration and Social services				
3-digits					
244	Pharmaceutical industry				
271	Iron industry				
722	Software industry				

Legend: 1% 5% 10%

[22] We apply a correction according to the Bonferroni's criterion in order to avoid distortions in our LISA indicators.

Table 8: Local statistics

Density variables; Brussels excluded;

Weights : $1/d^2$; pseudo-significance levels : 5% ; Years 1996-97.

	NACE code	15	17	22	24	25	26	28	29	31	32	33	34	45	50	70	72	73	75	244	271	722
District code	**Labor** **R&D**	Manufacture of foodstuffs, alcohol and tobacco	Production of textiles, clothing, leather and shoes	Paper and paper board industry, publishing and printing house	Chemical industry	Manufacturing of rubber and plastic products	Production of other non-metallic mineral products	Metallurgy and manufacture of metal products	Manufacture of machines and equipment tools	Manufacture of electrical and electronic equipment and	Manufacture of radio, TV and communication tools	Manufacture of clocks, medical care tools and other precision	Manufacture of means of transport	Constructions	Commerce of means of transport	Real estate industry	Computer and data processing industry	Research and Development (service)	Public Administration and Social services	Pharmaceutical industry	Iron industry	Software industry
11	Antwerpen																					
12	Mechelen																					
13	Turnhout																					
23	Halle-																					
24	Leuven																					
25	Nivelles																					
31	Brugge																					
32	Diksmuide																					
33	Ieper																					
34	Kortrijk																					
35	Oostende																					
36	Roeselare																					
37	Tielt																					
38	Veurne																					
41	Aalst																					
42	Dendermonde																					
43	Eeklo																					
44	Gent																					
45	Oudenaarde																					
46	Sint-Niklaas																					
51	Ath																					
52	Charleroi																					
53	Mons																					
54	Mouscron																					
55	Soignies																					
56	Thuin																					
57	Tournai																					
61	Huy																					
62	Liège																					
63	Verviers																					
64	Waremme																					
71	Hasselt																					
72	Maaseik																					
73	Tongeren																					
81	Arlon																					
82	Bastogne																					
83	Marché en																					
84	Neufchateau																					
85	Virton																					
91	Dinant																					
92	Namur																					
93	Philippeville																					

Legend: *high-low* *low-high* *high-high*

Table 9: Local statistics

Density variables; Brussels excluded;

Weights: first-order contiguity; pseudo-significance levels: 5%; Years 1996-97.

	NACE code	15	17	22	24	25	26	28	29	31	32	33	34	45	50	70	72	73	75	244	271	722
District code	**Labor R&D**	Manufacture of foodstuffs, alcohol and tobacco	Production of textiles, clothing, leather and shoes	Paper and paper board industry, publishing and printing house	Chemical industry	Manufacturing of rubber and plastic products	Production of other non-metallic mineral products	Metallurgy and manufacture of metal products	Manufacture of machines and equipment tools	Manufacture of electrical and electronic equipment and	Manufacture of radio, TV and communication tools	Manufacture of clocks, medical care tools and other precision	Manufacture of means of transport	Constructions	Commerce of means of transport	Real estate industry	Computer and data processing industry	Research and Development (service)	Public Administration and Social services	Pharmaceutical industry	Iron industry	Software industry
11	Antwerpen																					
12	Mechelen																					
13	Turnhout																					
23	Halle-																					
24	Leuven																					
25	Nivelles																					
31	Brugge																					
32	Diksmuide																					
33	Ieper																					
34	Kortrijk																					
35	Oostende																					
36	Roeselare																					
37	Tielt																					
38	Veurne																					
41	Aalst																					
42	Dendermonde																					
43	Eeklo																					
44	Gent																					
45	Oudenaarde																					
46	Sint-Niklaas																					
51	Ath																					
52	Charleroi																					
53	Mons																					
54	Mouscron																					
55	Soignies																					
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57	Tournai																					
61	Huy																					
62	Liège																					
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81	Arlon																					
82	Bastogne																					
83	Marché en																					
84	Neufchateau																					
85	Virton																					
91	Dinant																					
92	Namur																					
93	Philippeville																					

Legend: *high-low* *low-high* *high-high*

- **Appendix C: Moran Scatterplots**