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Externalities, knowledge spillovers and the spatial distribution of innovation

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Abstract

The aim of the paper is to investigate the process of spatial agglomeration of innovation and production activities and to assess the extent to which the degree of specialisation or diversity externalities in the area may affect the innovative output in a particular local industry. The analysis is carried out thanks to an original databank on innovation and production activity across 85 industrial sectors and 784 Italian Local Labour Systems, which are groupings of municipalities characterised by a high degree of self-contained flows of commuting workers. According to the global and local indicators of spatial association there are clear signs of spatial correlation in the distribution of innovation activities. The econometric analysis shows that the two types of externalities – specialisation and urbanisation economies – are both effective. Moreover, we find evidence for knowledge spillovers since technological activities of a local industry influence positively innovations of the same sectors in contiguous areas.

Introduction

Since last century economists have investigated into the determinants of firms' tendency to concentrate in specific areas. In his seminal contribution Marshall (1890) argued that a firm enjoys external economies by localising close to other firms since it can take advantage from the division of labour, the exchange of input, expertise and information. The role of these self-reinforcing mechanisms, which generate increasing returns specially in the process of knowledge creation and transfer, has been emphasised in more recent times by several authors (see, among others, Romer, 1986; Arthur, 1988; Krugman, 1991; Lucas, 1993). Consequently, a higher attention is now offered to the agglomeration process of technological activities and to its relationship with the spatial distribution of production.

A recent stream of the literature has explored extensively the nature of the mechanisms which generate a local and cumulative process of knowledge creation and diffusion innovation and has singled out two types of external economies (among others, Feldman and Audretsch, 1999). The first type concerns specialisation externalities, which operate mainly within a specific industry, associated to the contributions by Marshall. The second type is diversity externalities that favour the creation of new ideas across sectors, as originally suggested by Jacobs (1969). On the one hand, Marshall observes that industries specialise geographically because proximity favours the intra-industry transmission of knowledge. On the other hand, Jacobs believes that the variety of local activities plays a major role in the innovation process given that it enhances the economy's capacity of adding still more goods and services.

An interesting extension asserts that the specialisation and diversity externalities may also occur within the complementary industries which share the same science base with the sector considered. A more specific hypothesis on the role played by diversity externalities asserts that they are more likely to operate within metropolitan areas and this is why they are often labelled urbanisation externalities. The idea is that big urban agglomerations attract a large and differentiated variety of activities and thus become particularly suitable as breeding place for innovations (Glaeser et al., 1992; Brouwer et al., 1999). A second interesting specification conceives that diversity externalities are more powerful for high-tech sectors, where the pace of technological change is higher and where cross fertilisation from outside the core industry is crucial for breakthroughs in product and process innovations (Henderson et al., 1995).

Another important issue recently faced by the literature is the role of local versus nonlocal relations in the process of knowledge transmission and it is specifically addressed in several contributions to this volume (Rallet and Torre, this volume; Oinas, this volume). One view (for example, Coe and Helpman, 1995) asserts that technological progress is a public good and therefore knowledge spillovers are not locally bounded but can freely move across borders. In contrast with this position, a growing literature emphasises the local nature of knowledge which is still costly and difficult to transmit across areas (Jaffe et al., 1993). Spatial proximity helps firms in the process of information sharing and knowledge diffusion and it leads to the creation of technological enclaves.

In this paper we try to incorporate these issues in an encompassing empirical model which will be used to estimate the influence of specialisation and diversity externalities on the spatial distribution of innovative activities. We also examine the degree of spatial association in the distribution of technology given that it is very likely that innovative activity in a certain area is influenced by the technological performance of its neighbours, More precisely, we directly explore the existence of knowledge spillovers by introducing among the explanatory variables of our model the spatially lagged technological activities. Further, we explore the role of complementary industries, which share the same science base, in terms of their degree of both specialisation and diversity. Finally, we test whether there is any significant difference in the impact of diversity externalities with respect to the dimension of cities and the propensity to innovate of the sectors involved.

The empirical application refers to the case of 784 Italian Local labour System (LLS) which represents an appropriate spatial unit to analyse the effects of technological externalities since they are defined as groupings of municipalities characterised by a high degree of self-contained flows of commuting workers. Concerning the sectoral breakdown, our data are defined for 85 industrial sectors. Data on innovative activity comes from an original database set up by the Centre for North South Economic Research (CRENoS) on the basis of patent applications to the European Patent Office (EPO) from 1978 to 1995, classified by inventors' residence. The very detailed spatial and sectoral split of our data base allows for a particularly rich analysis about the effects of external economies on the distribution of innovative activities.

The structure of the paper is as follows. First, we review the recent literature on spatial externalities. Then, we briefly present the main features of our data base on innovative activity in Italy and investigate the problem of spatial auto-correlation. The theoretical framework is outlined in the subsequent section before we present the econometric results. Concluding remarks are presented in the last section.

Specialisation and diversity externalities

The long-standing debate on the existence of various forms of agglomeration economies focuses on the idea that self-enforcing mechanisms are spatially bounded. The literature has distinguished between two main categories of externalities. The former affect mainly the production side and are usually divided into localisation (Marshall, 1890) and pecuniary (Krugman, 1991) externalities. They can materialise as an appropriate agglomeration pattern which facilitates asset-sharing like, for example, the provision of specific goods and services according to an input-output framework (Bartelsman et al., 1994). Or they can emerge as a more convenient set of relative prices and qualities of the labour force (labour pooling) and of primary and intermediate goods (Ellison and Glaeser 1999) or, finally, as a set of useful ad hoc infrastructures (such as roads, pipes and telecommunication networks).

The second type of economies – the technological externalities – are more related with the tacit and local nature of knowledge. In this case agglomeration in a specific place is a rational response adopted by firms to ease the exchange of information and expertise. Indeed, despite the great progress in information technologies, knowledge is still costly and difficult to transmit across areas (Jaffe et al., 1993; von Hippel, 1995). Consequently, local collective learning processes, mainly based on tacit knowledge, may constitute an important premise for the competitive advantage as well as for the potential attractiveness of regions (Lawson and Lorenz, 1999; Capello, 1999; Maskell and Malmberg, 1999).

These increasing returns in spatial form favour the formation of regional innovation districts and, together with localisation externalities, may contribute to the creation of local production systems. How much these two forms of local systems are related, what is the nature of the externalities and how they affect local growth are central questions faced, with various methodological approaches, by researchers in the fields of industrial, regional and growth economics (see Ottaviano and Puga, 1998; Brulhart, 1998, for updated surveys on the new economic geography literature). For our purpose it may be useful to distinguish four research directions.

The first direction is represented by the long standing literature on 'spatial innovation networks' and 'innovative milieu' (Camagni, 1991; Cooke and Morgan, 1994) and 'industrial districts' (Brusco, 1982; Pyke et al., 1990). This approach usually grounds its research on case studies of specific areas which allow for detailed analyses of the complex interacting forces that shape the development of a local system (i.e., a combination of economic, social and cultural elements).

A second line of research investigates the spatial distribution of innovative activities in larger economic systems and tries to identify common trends and special patterns in the clustering of innovation. These studies have analysed US cities and states (Jaffe et al., 1993; Feldman, 1994; Audretsch and Feldman, 1996) and the European regions (Breschi, 1997; Caniels, 1999; Paci and Usai, 2000a; Verspagen, 1999). A substantial effort has been devoted to the set up of new databanks on innovation activities, measured by patent applications, patent citations and new products announcements.

The third approach directly assesses the nature and the effects of externalities on the economic growth of local systems. The empirical applications have focussed again mainly on the US case (Glaeser et al., 1992; Henderson et al. 1995; Lamorgese, 1997) and have reached contrasting results on the relative importance of specialisation and diversity externalities. A common shortcoming in the empirics of these studies is the lack of a specific variable to measure innovation activities, which makes the assessment of the role of technological externalities rather indirect.

The fourth line of research, which is the benchmark for our contribution, investigates directly the nature of the spillovers between production and innovation activities through a theoretical framework where the spatial agglomeration of innovation depends, among other factors, on the degree of specialisation of the local production system. This approach has been applied to the case of US cities and states by Audretsch and Feldman (1999) and Kelly and Hageman (1999), respectively. The most striking, and probably unexpected, result of both analyses is that there is no evidence of specialisation externalities, whilst diversity externalities are at work in the case of US metropolitan areas. In other words, in the United States innovation in a specific sector exhibits strong spatial clustering independently of the distribution of manufacturing activity. Contrary to this result, Paci and Usai (2000a) show that in the European regions there exists a positive association between the spatial distribution of technological activity and productive specialisation, a clear even though indirect support to Marshall's idea of externalities.

The spatial distribution of innovative activity

Our empirical analysis is based on a new database on innovative activity in the European regions from 1978 to 1995 set up by the Centre for North South Economic Research (CRENoS). Innovative activity is measured by means of patent applications to the European Patent Office (EPO). In the case of Italy, data refer to 784 Local Labour Systems (LLS) identified by ISTAT (see Sforzi, 1997) as groupings of municipalities with a high degree of self-containment of the labour forces' flows. At the European level, Cheshire and Hay (1989) have introduced a similar concept, that of Functional Urban Regions. This high level of spatial split appears particularly fruitful for the analysis of knowledge externalities since, as we have already stressed, it is likely that they are locally bounded and linked to the production activities within the area where workers live.

To attribute each innovation to a LLS we use the inventor's address, rather than the residence of the proponent which mainly coincides with the location of the headquarters of the firm. The former information is now commonly believed (see, for example, Breschi, 1997) to provide a more precise indication of the exact geographical origin of the innovative activity given that, in this way, one can detect the innovation activity performed in those plants located away from the main site of the company.

Patent data, originally classified according to the International Patent Classification (IPC), have been referred to the corresponding industry of manufacture thanks to the Yale Technology Concordance (see Evenson, 1993) which attributes each patent proportionally to the different sectors where the innovation may have originated. More details on the construction of the database and on the controversial issues regarding the use of patent statistics as technological indicators are given in Paci and Usai (2000b).

Figure 1 provides a clear description of the spatial distribution of innovative activities across the Italian LLS based on the average value of patents for the period 1990–1991. It is immediately visible that innovation is an extremely dispersed and, in the case of Italy, dualistic phenomenon which divides North and South. There are 469 local areas which have not performed patenting activity, mostly located in southern Italy where just 4% of total innovative activity is originated.

Conversely, more than 80% of total patenting is concentrated in the North (around 50% in the Northwest and 30% in the Northeast). The most innovative area is Milan where 460 patents have originated in the two years 1990–1991. Other large cities in the North, such as Turin, Bologna, Genoa, Venice and Florence are among the top innovation centres as well as some important metropolitan areas in the Centre (Rome) and in the South (Bari, Naples and Catania). However, among the most innovative areas one finds not just large cities but also some important districts of the Northeast, such as Pordenone and Montebelluna, the former specialised in domestic appliances and the latter in sportswear.

From Figure 1 it is clear that the distribution of innovative activity tends to follow an explicit spatial pattern. First, there appear some quite large clusters (which are quite linked together) around the main metropolitan areas in the North, that is Turin, Milan, Bologna and Florence. Moreover, some other relatively 'isolated' and smaller innovative clusters emerge in the Northeast, the one with Padua, Vicenza, Treviso and Venezia, and the other one with Udine and Pordenone. Some further evidence in favour of a process of spatially defined technological diffusion comes also from the appearance of an aggregation of systems with medium-high innovative propensity along the fast growing Adriatic belt: the cluster of Fabriano with Iesi and Recanati. It is also possible to recognise some innovative cluster in the South, even though at a very modest level of innovativeness, such as the areas around Naples, Bari and Catania.

In other words it is clear that local systems with high technological activity are often close with each other and so are those systems with no technological activity. This suggests the presence of spatial dependence, that is an apparent relationship between innovative activity in contiguous areas. One may obviously interpret this relationship as a sign of spatial externalities which spill over from one local area to another one which is nearby.

To assess this point more precisely, in Table 1 we report the Moran test computed on the basis of a spatial weight matrix which reports all the contiguities among our 784 local systems. The results clearly show the presence of positive spatial association in the distribution of innovative activities: the Moran's I being 0.38 which makes the probability of error rejecting the hypothesis of absence of spatial autocorrelation close to null. Moreover, the spatial association holds, even though decreasing, also for higher orders of contiguity, the Moran's I being 0.32 for the second order contiguity and 0.27 for the third order.

The index above is a global measure of spatial dependence and therefore unsuitable to detect the degree and the nature of spatial correlation at the local level. Indeed, considering the association between each region and its neighbours, we can identify four types of spatial correlation: high-high, low-low, high-low, low-high. The first two show the presence of positive association, while the second two signal a negative spatial dependence. Figure 2 reports the

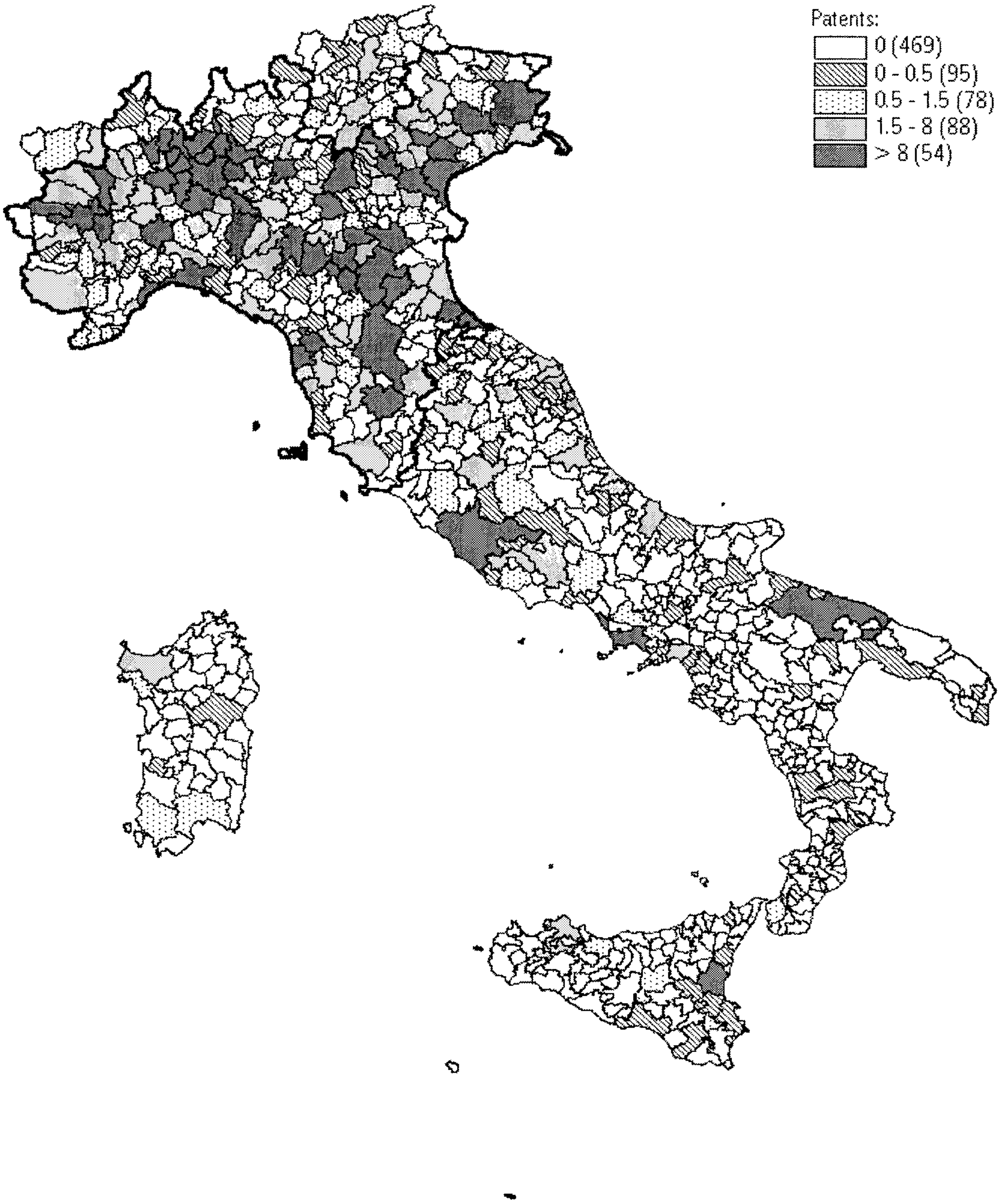

Figure 1. Spatial distribution of innovative activity. Total patents, annual averages (1990–1991).

Table 1. Spatial autocorrelation of innovative activity I-Moran for different contiguity orders (patenting per capita)

	Normal approach			Permutation approach	
	I	Z-value	Prob.	I	Prob.
First-order contiguity	0.379	16.49	0.00	0.379	0.001
Second-order contiguity	0.328	21.20	0.00	0.328	0.001
Third-order contiguity	0.273	21.09	0.00	0.273	0.001

Moran scatterplot map based on the local indicator of spatial association (LISA) suggested by Anselin (1995) to pinpoint local patterns of concentration (‘hot spots’). It should be noticed that the reported LISA are not all significant from a statistical point of view. Not surprisingly, most positive associations (457 out of 784) are between systems with low level of technological activity (see the white areas in Figure 2) and they are obviously located mainly either in the South or in the mountain regions of the North. More interestingly, there appear several local labour systems in the North, characterised by a high level of technological activity, positively related with neighbouring areas. The high-high spatial correlation is particularly significant in the following areas, the whole region which stretches from Turin to the hinterland of Milan, with some appendices towards Piacenza and Parma; the Northeast area from Udine to Treviso, passing by Padua and Vicenza; the area which goes from Bologna to Florence. Around these clusters, as expected, one notices a ring of local systems characterised by a negative low-high association, which acts as a border area with respect to the high level regions. Finally, it is interesting to notice the presence of around 50 highly innovative local systems surrounded by areas with low technological activity, most notably some areas in the South where clearly the positive spillover mechanism is not strong enough and is bounded to the main area.

The empirical model

Our main purpose is to assess the extent to which technological activity in a local industry is affected by the degree of production specialisation in the same local industry (Marshall externalities) and by the degree of industrial diversity in the local system (Jacobs externalities). An interesting extension is the assessment of the impact of complementary industries which share the same science base both in terms of specialisation and in terms of diversity. We also include some control variables to take into account differences which may arise due to the amount of technological opportunities that characterises each industry, the dimension of the local labour system and the sectoral characteristics. Let us now discuss in details the definition and the expected impact of each explanatory variable included in our model.

To measure Marshall externalities, the most commonly used index is the production specialisation index (PS) based on employment data (E) which is specific to each local industry:

$$PS_{ij} = \left[\frac{E_{ij}}{\sum\limits_{i} E_{ij}} \right] \Bigg/ \left[\frac{\sum\limits_{j} E_{ij}}{\sum\limits_{i} \sum\limits_{j} E_{ij}} \right]. \tag{1}$$

A positive and significant sign of its coefficient is interpreted as evidence of the fact that innovations are bound to arise within those sectors in which the production of local system is specialised. For the empirical analysis the index has been standardised using the formula (PS$-$1)/(PS$+$1), so that it is constrained within the interval ($-$1,1).

To capture the crucial effects of diversity externalities a measure for the degree of variety which characterises each local system is needed. To this aim, we use the production diversity index (PD) for the whole local system based on the reciprocal of the Gini coefficient:

$$PD_j = \left[\frac{2}{(n-1)Q_n} \sum_{i=1}^{n-1} Q_i \right], \tag{2}$$

where Q_{i} is the cumulative sum of employees (E) up to sector i when sectors are listed in increasing order. The index is defined within the interval (0,1) and it increases together with variety. The index PD allows for testing Jacobs hypothesis, according to which a higher level of diversification of the local system favours innovative activity. Given that the Gini coefficient is a measure of concentration, an increase of its reciprocal implies that diversity grows and therefore we interpret a positive and significant sign on its coefficient as evidence for the presence of diversity externalities. In several studies, due to the lack of data, the same index is used to discriminate between Marshall and Jacobs externalities (see for example Lamorgese 1997, even though in a different setting). Conversely, our data set gives us the advantage of testing separately the two hypotheses by means of more appropriate indicators.

It has been suggested that the effects of specialisation and diversity economies on the distribution of innovative activities can also take place within the complementary industries which share the same basic scientific knowledge with the sector considered. Therefore, following Audretsch and Feldman (1999), we have also included the specialisation and diversity indexes for the science base clusters based on the Yale survey. This survey provides an assessment of the relevance of basic scientific research in biology, chemistry, computer science, physics, mathematics, medicine, geology, mechanical engineering, and electrical engineering. In the light of such an assessment, Feldman and Audretsch identify six groups of industries which share similar rankings for the importance of the academic discipline above. Such six clusters are Agra-business, Chemical engineering, Office machinery, Industrial machinery, High-tech computing, Biomedical. Accordingly, the index of specialisation in the science base cluster (SBS) is an indicator of the degree of specialisation of the local district in complementary industries to sector i:

$$SBS_{ij} = \left[\frac{E_{ij}^k}{\sum\limits_{i} E_{ij}} \right] \Bigg/ \left[\frac{\sum\limits_{j} E_{ij}^k}{\sum\limits_{i} \sum\limits_{j} E_{ij}} \right]. \tag{3}$$

where $E_{ij}^k = \sum_i E_{ij}^k - E_{ij}, k = 1 \ldots 6$ and $i \in k$. This index is computed in the standardised form too. We interpret a positive and significant sign of the coefficient of SBS as a further signal of the importance of specialisation (even though in near-by industries) and therefore of Marshall externalities.

The second science base index refers to the degree of diversity within the science base cluster (SBD) which is identified for each local district and each sector. The formula

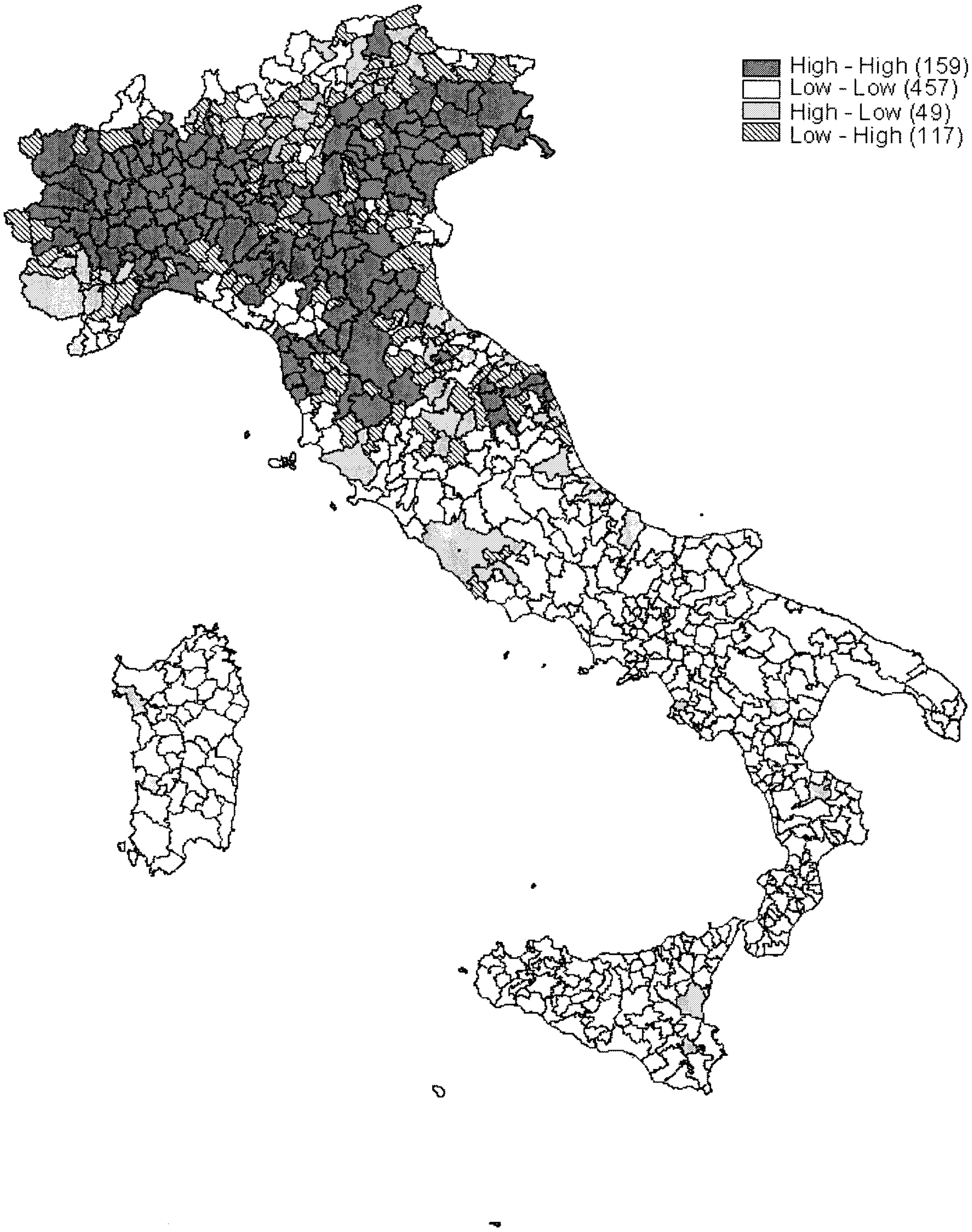

Figure 2. Local indicator of spatial association for innovative activity. Moran scatterplot map.

is, again, based on the reciprocal of the Gini coefficient referred to employment within the sectors which constitute the cluster k defined above:

$$SBD_{ij} = \left[\frac{2}{(n^k - 1) Q_n^k} \sum_{i=1}^{n^k - 1} Q_i^k \right], \tag{4}$$

where Q_i is the cumulative sum of employees (E) in cluster k up to sector i when sectors are listed in increasing order. In other words, thanks to this variable we are able to assess the role of diversity also among those sectors which, due to the sharing of the same common science base, are likely to cross-fertilise themselves more easily. A positive significant sign will be read as a further evidence of the presence of diversity externalities.

We have, finally, included a set of control variables to take into account some specific feature of the local systems and of the industries. First, the level of technological opportunity (TO), specific to each sector, to check if the agglomeration process of innovations depends on the level of available knowledge and innovations in each sector:

$$TO_i = \sum_j P_{ij}, \tag{5}$$

where P_{ij} is the number of patents in sector *i* and LLS *j*. This index is supposed to provide a measure of the amount of specific knowledge available at the national level for further development and research within a certain sector. We expect a positive sign on its coefficient.

Secondly, we introduce a dummy variable for metropolitan areas (DM) identified by ISTAT based mainly on population data. This allows us to discriminate between main urban areas and small local districts and, therefore, to test whether, as argued by Glaeser et al. (1992), Jacobs externalities are more likely to operate within metropolitan areas, where there coexist many manufacturing sectors.

Thirdly, we define a high tech sectors dummy (DHT) which equals unity for those sectors with a quota of innovative firms above the threshold of 40% according to the Italian national survey on technological activity (ISTAT 1998), and zero otherwise. The main aim of such a distinction is to test whether Jacobs externalities are more powerful for high-tech dynamic sectors, where cross fertilisation from outside the core industry is crucial for breakthroughs in product and process innovation, as in Henderson et al. (1995) for the US case.

We have thus specified an encompassing model where the dependent variable y_{ij} (i.e. innovative activity in sector *i* and local labour systems *j* divided by population) is affected by several explanatory variables referring to: (i) characteristics of local industries, (ii) specific features of the local system common to all sectors, (iii) characteristics of the industrial sector common to all systems. The general model is as follows:

$$\begin{aligned} u_{ij} &= \alpha + \beta PS_{ij} + \chi PD_j + \phi SBS_{ij} + \gamma SBD_j + \\ &\quad + \delta TO_i + \chi_1 PD_j * DM + \\ &\quad + \chi_2 PD_j * DHT + \varepsilon_{ij}. \end{aligned} \tag{6}$$

Moreover, we are interested in testing a spatially dynamic form, with the inclusion of spatially lagged variables which provide a test for the presence of some type of dependence between the innovative activity under exam in one area and the same phenomenon in other contiguous spatial units (see Anselin 1988). This spatial autoregressive models, in other words, enable us to evaluate whether there exist knowledge spillovers which flow across LLS borders.

Econometric results

The econometric estimation is based on 24 820 observations obtained by combining 85 sectors at the three-digit level and 292 local system out of the 784 Italian LLS. In order to perform the spatial regression analysis we have, therefore, considered all local systems belonging to the Italian northern regions which constitute a contiguous area whose border is indicated by a bold line in the previous Figure 1. We have also excluded the two small alpine regions of Valle d'Aosta and Trentino because they have a negligible technological activity. It is important to stress that all the highest innovative systems are included in our set but for few districts situated in the Adriatic belt (Fabriano and Recanati, for example) and for the main metropolitan areas in the South.

The dependent variable used in the estimation is computed as an annual average of patents per capita over the period 1990–1991. The choice of weighting the number of patents with a dimensional variable, which corrects for the high heterogeneity in the dimension of the territorial units, is motivated by potential problems of heteroskedasticity. The employment data used to calculate the specialisation and diversity indexes are from 1991 Census.

The White-robust OLS estimates of the basic function (6) are reported in the first column of Table 2. The positive and statistically significant coefficient of industry specialisation (β), the basic Marshall externalities measure, suggests that innovative activity in a certain industry is higher when it is located in an area specialised in that industry. On the one hand, this result is in contrast to Audretsch and Feldman (1999) and Kelly and Hageman (1999) who, with different methodologies and data sets, reach the same conclusion: innovation activities do not follow the same geographical distribution of production in the United States. On the other hand, this outcome confirms previous studies where a correlation between specialisation in production and innovation is found among the European regions (Paci and Usai, 2000a) and among a different sample of LLS in Italy (Paci and Usai, 2000b). The Italian situation proves, unsurprisingly, different to the American case most probably because of the substantial differences in the industrial structure between the two countries. In particular, Italy is characterised by a large presence of small and medium enterprises in the traditional sectors, where innovation is more informal and incremental in nature and it is mainly performed within the operative plants. This may explain why innovation and production are usually located in the same place. On the contrary in the US, there is a great number of multinationals and large firms, whose innovative activity is more formal and performed into R&D laboratories which have not got to be necessarily located near the headquarters or the production sites.

As far as the role of diversity is concerned, the degree of variety appears to affect innovative activity with a positive and significant impact when measured at the local system level. In other words, when the diversification across industries in the local system is higher, Jacobs externalities are at work and innovative capacity is, consequently, encouraged. However, the interpretation of such a coefficient is not independent from the coefficients of the multiplicative dummies, which are all positive and statistically significant. This signals the importance of differentiating diversity externalities according to the characteristics of the local systems and of the industrial sectors. This differentiation is summarised in the last rows of Table 2 where the impact of diversity (the coefficient of PD) is reported with respect to three cases for different specification of our empirical model. As for equation (6) we notice that Jacobs externalities are more robust when one combines high tech sectors in metropolitan dis-

Table 2. Econometric estimates

Explanatory variables			(1)	(2)	(3)	(4)	(5)	(6)
	Constant	α	−0.026	−0.017	−0.017	−0.017	−0.019	−0.014
			(0.004)[a]	*(0.004)*[a]	*(0.004)*[a]	*(0.004)*[a]	*(0.004)*[a]	*(0.005)*[a]
PS	Production specialisation	β	0.029	0.024	0.023	0.023	0.025	0.024
			(0.003)[a]	*(0.003)*[a]	*(0.003)*[a]	*(0.003)*[a]	*(0.004)*[a]	*(0.003)*[a]
PD	Production diversity	χ	0.202	0.152	0.149	0.149	0.153	0.162
			(0.017)[a]	*(0.017)*[a]	*(0.017)*[a]	*(0.017)*[a]	*(0.017)*[a]	*(0.021)*[a]
SBS	Science base specialisation	ϕ	0.012	0.008	0.008	0.008	0.008	0.008
			(0.004)[a]	*(0.003)*[b]	*(0.003)*[b]	*(0.003)*[b]	*(0.003)*[b]	*(0.003)*b
SBD	Science base diversity	γ	0.017	0.005	0.004	0.003	0.006	0.005
			(0.012)	*(0.013)*	*(0.012)*	*(0.013)*	*(0.013)*	*(0.013)*
TO	Technological opportunity	δ	0.002	0.001	0.001	0.001	0.001	0.001
			(0.000)[a]	(0.000)[a]	*(0.000)*[a]	*(0.000)*[a]	*(0.000)*[a]	*(0.000)*[a]
PD*DM	Production diversity * metropolitan areas dummy	χ^1	0.030	0.045	0.052	0.052	0.044	0.043
			(0.033)	*(0.029)*	*(0.029)*[c]	*(0.029)*[c]	*(0.029)*	*(0.029)*
PD*DHT	Production diversity * high-tech sectors dummy	χ^2	0.144	0.123	0.127	0.124	0.119	0.124
			(0.025)[a]	*(0.025)*[a]	*(0.024)*[a]	*(0.024)*[a]	(0.025)[a]	(0.025)[a]
BPOP(-1)	First order lagged dep. var.			0.429	0.389	0.397	0.431	0.431
				(0.052)[a]	*(0.054)*[a]	*(0.058)*[a]	*(0.052)*[a]	*(0.052)*[a]
BPOP(-2)	Second order lagged dep. var.				0.159	0.166		
					(0.058)[a]	*(0.061)*[a]		
BPOP(-3)	Third order lagged dep. var.					−0.062		
						(0.10)		
PS(-1)	Lagged production specialisation						−0.006	
							(0.004)	
PD(-1)	Lagged production diversity							−0.027
								(0.028)
DHT=0, DMET=1		$\chi + \chi^1$	0.232	0.197	0.201	0.201	0.197	0.205
DHT = 1, DMET = 0		$\chi + \chi^2$	0.346	0.275	0.276	0.273	0.272	0.286
DHT = 1, DMET = 1		$\chi + \chi^1 + \chi^2$	0.376	0.320	0.328	0.325	0.316	0.329
Adjusted R^2			0.204	0.249	0.252	0.252	0.249	0.249
LM test for spatial autocorrelation			992.6	416.2	311.9	313.6	425.0	421.5

Dependent variable: patent per 100 000 inhabitants (BPOP).
OLS estimates. White robust standard error in parentheses. Significance levels: a=1%, b=5%, c=10%.
Number of observations: 24,820

tricts (the impact being $\chi + \chi_1 + \chi_2 = 0.38$) whilst they are still significant but definitely lighter for low tech sectors located in small areas (in that case $\chi = 0.2$). Interestingly, these results are in line with the findings of Glaeser et al. (1992) and Henderson et al. (1995) for large towns and high tech sectors in the US, respectively.

Marshall and Jacobs externalities within the science base cluster, on the contrary, are positive but only the former is statistically significant confirming the importance of qualifying the nature and the width of technological spillovers (see Paci and Usai, 2000b).

In the next columns (2–4) we introduce a spatially lagged dependent variable with different levels of contiguity in order to test the importance of externalities which cross the borders of the local labour systems. The need for a spatially dynamic representation is also required by the evidence of the LM test which detect the presence of spatial autocorrelation. Results in column 2 and 3 show that this inter-local labour systems externalities are significantly positive until the second order of contiguity (coefficients are around 0.4 and around 0.15 for the first and the second order of contiguity, respectively). Interestingly, in column 4 we discover that such technological spillovers are not spatially unbounded, but that they actually die out with increasing distances from the core area (the coefficient of the third order lag being negative but not significant).

We have finally examined how various degrees of specialisation and diversity in contiguous areas may affect the technological activity of a local industry. Results in column 5 show that innovative activity in a specific sector and area is negatively associated to productive specialisation in the same sector in contiguous areas. This result suggests that Marshall externalities are very localised and they work only in a restricted area which, in our empirical setting, corresponds to the self-contained local labour system. In column 6, diversity effects also prove to work only within the boundary of the LLS.

In conclusion, the spatial externalities evidenced above should be interpreted as general flows of knowledge from one system to others systems nearby. Some additional research is required to achieve a complete understanding of the nature of this particular phenomenon and its spatial-dynamic properties also because the spatial autocorrelation, although moderated, has not been completely removed (see LM test).

Conclusions

In this paper we have investigated the controversial effects of industrial diversity and specialisation on the spatial agglomeration of innovative activities. The more recent literature has distinguished between two types of externalities: Marshall (specialisation) or Jacobs (diversity) economies. However, at the empirical level, the lack of data has prevented to clearly discriminate between the two types of externalities and most studies have simply relied on a single measure to assess whether Marshall or Jacobs externalities are prevailing. In our opinion it is important to make clear that these two externalities are not necessarily opposed, since specialisation is a particular feature of a certain sector within a local system whilst diversity is a characteristic of the whole area. Therefore we may have a huge number of combinations between different levels of specialisation in a local sector and degrees of diversity in the area. This is why, thanks to a rich and detailed database on innovation and production at the local and sectoral level, we have separately account for the two types of externalities.

The most important result of our econometric analysis is that innovative activities in a local industry is positively affected by both Marshall externalities associated to productive specialisation in the same sector and Jacobs externalities associated to the degree of diversity of the local system. This result contrasts with some recent literature on the case of the United States where the two types of externalities have been considered as contrasting and the specialisation economies were not found. Further, with respect to the Jacobs externalities, our findings indicate that they play a different role depending on the nature of the local district (whether it is a metropolitan area or not) and on the type of industry (high vs low tech sectors). More specifically, such externalities appear more powerful in high tech sectors and in metropolitan areas.

A second important issue addressed in our analysis is the presence of technological spillovers across contiguous areas. More precisely, the spatial autoregressive specification of the model shows that there exist technological externalities across borders which implies that innovative activity in a local system is positively influenced by the level of innovativeness of contiguous systems. However, the spatially dynamic estimations point out that technological spillovers are not spatially unbounded since they actually die out with increasing distances from the area considered. Moreover, specialisation and diversity externalities prove to be active only within the local labour systems.

In conclusion, the various evidence gathered is concordant in emphasising the positive role of specialisation and diversity externalities on the spatial distribution of innovative activities and the locally bounded nature of such technological spillovers. Our results shed some light on the relations between the process of knowledge creation and diffusion in a certain area and the industrial characteristics of the local production system. Therefore, although at the present stage our research does not directly challenge dynamic problems, it gives helpful hints on which features of the local systems are more favourable to start a virtuous circle of technological progress and regional development.

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