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Spatial Patterns of Innovation and Trade Competitiveness The Case of Italy

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Abstract

A renewed interest has been growing recently for the spatial dimension of trade and knowledge flows. Several contributions have shown that knowledge proximity matters in mediating flows of knowledge and that knowledge spillovers tend to occur within limited geographical boundaries. Theoretical works have also shown that geographical concentration of knowledge spillovers may play a fundamental role in shaping national and regional patterns of specialisation and comparative advantages through cumulative processes. In spite of such advances, still few empirical works exist attempting to verify the relationship between *localised* knowledge spillovers and regional patterns of trade specialisation and comparative advantages. This paper aims to provide a first empirical assessment of the relationship between localised technological externalities and trade performance in high technology industries in Italy. The data used in the analysis are based on the European Patent Office data base and on trade statistics from the five digit SITC classification, and are spatially referenced to the Italy NUT3 regional partition. The analysis adopts a spatial econometric approach where knowledge externalities are modelled through the inclusion in regression estimates of spatially lagged variables for innovations. Results from econometric estimates provide some evidence of impact of local technological spillovers on regional trade performance. Local knowledge spillovers appear to positively affect the trade performance in the industrial automation and instruments sectors. No evidence of localised effects of technological externalities on trade competitiveness is instead found in most electronics sectors.

Keywords: innovation, knowledge spillovers, trade competitiveness
JEL: O3 Technological change, F1 International trade.

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1. Aim of the paper

This paper aims at providing an empirical examination of the relationship between international trade and innovative activities at the regional level, by adopting a spatial econometric approach. In recent years, interest on the spatial dimension of trade and knowledge flows has rapidly increased. On the one hand, some authors have pointed out that the geographical concentration of knowledge spillovers may play a fundamental role in shaping national and regional patterns of specialisation and comparative advantages (Grossman and Helpman, 1991). If knowledge flows only takes place within well defined spatial boundaries (national or regional), then some regions or countries will deepen their patterns of specialisation through cumulative processes given an initial technological endowment. On the other hand, a different line of research has attempted to measure knowledge and to trace knowledge flows. By analysing data on patent citations, Jaffe et al. (1993) show that patent citations do appear to be somewhat localised geographically, i.e. cited patents are likely to come from the same state as the citing patent, thus implying that a region or country does utilise knowledge created within it somewhat more readily than do more remote regions. In a similar vein, Jaffe (1989) has analysed the relationship between university research and patenting activity, showing that the extent of knowledge spillovers is affected by geographical distance: firms are likely to benefit more from R&D conducted in Universities located in their home states. More recently, Anselin, Varga and Acs (1997) have investigated the issue of local geographic spillovers between university research and innovative activity by small high technology firms using innovation counts for 125 metropolitan regions in the USA. Their results show that spillovers of university research have a positive and significant impact on regional rates of innovation and they extend over a range of 75 miles from the innovating region. Moreover, university spillovers appear to be particularly strong for innovations in the electronics and instruments sectors.

From a more theoretical perspective, other authors have investigated what are the properties of knowledge that can explain the localised nature of knowledge spillovers. Most contributions point out the fundamental role of *geographical proximity* in facilitating the transmission and the absorption of technological and scientific knowledge. Knowledge diffuses mainly through informal means, like interpersonal contacts, face-to-face communications, meetings, seminars, on-the-job training and other similar mechanisms, whose effectiveness decreases with the distance between agents (Pred, 1966; Feldman, 1994). In addition, the more the knowledge base is tacit, complex and part of larger systems, the more likely geographical proximity plays a relevant role in facilitating the transmission of knowledge. Conversely, the more the relevant knowledge base is codifiable, codified, simple and independent, the less likely is that spatial proximity plays an essential role in permitting the transfer of important pieces of knowledge (Winter, 1987; Breschi, 1998). In this respect, one can also argue that geographical patterns of

knowledge spillovers differ across sectors because their knowledge base- in terms of tacitness, codification, complexity and so on- differ depending on the industrial context and therefore proximity is likely to play either a highly important or a negligible role in mediating flows of knowledge (Breschi and Malerba, 1996).

In spite of these theoretical advances, still very few empirical works exist attempting to verify the relationship between *localised* knowledge spillovers and regional patterns of trade comparative advantages. The empirical literature that has addressed the role of technology in determining the patterns of trade specialisation is still largely based on a country dimension (van Hulst, Mulder and Soete, 1991; Amendola, Dosi and Papagni, 1993). Generally speaking, the results of these studies show the existence of significant links between technological and international trade performance of industrialised countries, even though a major flaw of such results is that they are observationally equivalent from the point of view of different theoretical explanations.

In this paper, we will address the issue of the links between technology and trade specialisation in a spatial context. More specifically, we aim to provide a first empirical evaluation of the extent to which localised knowledge spillovers can affect the patterns of trade comparative advantages of regions in high technology industries in Italy. To this purpose, the paper will analyse two basic sources of data: patent data from the European Patent Office database, on the one hand, and trade statistics (at the five-digit SITC classification), on the other hand. Both types of data have been spatially referenced to the Italy NUT3 regional partition, that corresponds to 95 administrative provinces. The analysis adopts a spatial econometric approach where knowledge externalities are modelled through the inclusion in regression estimates of spatially lagged variables for patenting activity that capture the effects of innovative activities taking place in adjacent provinces.

The paper is organised as follows. Section 2 provides a brief description of the data sources used in the paper and of the main methodological issues involved in using patent and trade data at the spatial level. Section 3 provides some preliminary evidence on the spatial distribution of trade and innovative activities by examining a large set of indicators of geographical concentration. Section 4 further explores the spatial structure of data and it discusses several spatial econometric issues. Section 5 provides a discussion of the main findings from the econometric estimates and section 6 concludes the paper with an evaluation of findings and steps for future research.

2. Data Sources and Methodology

This paper makes use of two basic sources of data:

- a) *Trade data*, i.e. the flows of *exports* of the 95 Italian provinces (corresponding to Eurostat NUT 3 regional partition) for the years 1988, 1991, 1993 and 1995. The data have been provided by the Italian National Institute of Statistics (ISTAT) and they have been processed by the Italian Agency for New Technologies, Energy and Environment (ENEA, Rome).
- b) *Patent data*, i.e. data on the *patenting* activities of the 95 Italian provinces for three sub-periods 1983-85, 1989-91 and 1993-95. The database has been elaborated by the Centre for Research on Internationalisation (CESPRI – Bocconi University, Milan) using the patent applications to the European Patent Office (EPO) by Italian firms and institutions seeking protection for their innovations in any of the 18 countries adhering to the Munich Convention which established the EPO.

Export data are classified by ISTAT according to the Standard International Trade Classification (SITC Rev. 3). Patent documents are instead classified by patent examiners of the EPO according to the International Patent Classification (IPC 6th edition)¹. A concordance table between SITC Rev. 3 and IPC codes has been built jointly by CESPRI-ENEA and Politecnico Milan for 11 high-technology sectors: pharmaceuticals, plastics, elastomers and fibres, fine chemicals and specialties, industrial automation, office machines, consumer electronics, electromedical instruments, electronic components, aerospace, measurement and control instruments, and optical instruments, systems and apparatus².

Some critical methodological issues must be dealt with regarding the spatial location of exports as well as patenting activities. With respect to trade data, it must be noted that a given flow of exports is attributed by ISTAT to the location where the selling activity has taken place. It is rather obvious that this may give rise to a bias in the spatial distribution of exports to the extent that production and distribution take place in different locations. For what concerns patent data, we had to face the problem of how attributing each patent document to the location where the corresponding innovative activity took place. Here, we followed two different strategies:

¹ All patent documents are indeed assigned by patent examiners of the EPO at least one classification code of the IPC. The IPC is an internationally agreed, non-overlapping and comprehensive patent classification system. Currently, the IPC refers to almost 60,000 individual codes (12-digits) and it may be used at different hierarchical levels (WIPO, 1994).

² The concordance table is available from the authors on request. The table can be also found in OECD (1994).

- i) each patent document was attributed to the province where the inventor of the patent was resident. In case of two or more inventors residing in different provinces, the patent itself was split proportionally to the number of inventors among the various provinces;
- ii) each patent document was attributed to the province where the establishment applying for the patent was located (as resulting from the applicant's address contained in patent documents).

Of course, both reported methods have pros and cons. On the one hand, the use of applicants' address is more likely to generate an overestimation of the actual level of spatial concentration of innovative activities. This can happen because patents are very often applied for by headquarters and R&D divisions located in urban and metropolitan areas, even though the innovative activity generating the invention took place in more decentralised establishments. On the other hand, using the inventors' residence is instead likely to produce a more diffused spatial distribution of innovations capturing, at least partly, innovative activities going on in more decentralised units. At the same time, however, this method can also lead to an underestimation of the actual degree of spatial concentration of innovations, especially if the inventors reside in different provinces, while working within the same establishment. In what follows, we use either one or the other (or both) methods of attributing patents to provinces, depending on the indicators analysed.

3. The Spatial Concentration of Trade and Innovative Activities

In order to analyse the spatial distribution of trade and innovative activities across the 95 Italian provinces in the 11 high-tech sectors we have considered three main indicators:

- ◆ C1 concentration ratio: the share of exports/patents held by the largest province in terms of either exports or patenting activity;
- ◆ C4 concentration ratio: the share of exports/patents held by the four largest provinces in terms of either exports or patenting activity;
- ◆ Herfindahl equivalent number (HEN): defined as the inverse of the Herfindahl index, given by the sum of the squared shares of patents/exports of all provinces.

Regarding the patenting activity, we have calculated the above mentioned indicators both with respect to the localisation of patenting firms and to the localisation of inventors (see above). Some remarkable features of the spatial distribution of trade and innovative activities in the high-sectors emerge from the analysis of the data (see Tables 1-3).

In the first place, it is quite evident that trade and innovative activities in the high-tech sectors are far more spatially concentrated than it happens for the manufacturing sector as a whole. The

C4 ratio of exports for all manufacturing sectors is around 35-36%, whereas the same ratio referred to the high-tech sectors is around 60%. (see Table 1). This result is also confirmed by the Herfindahl index that shows a degree of spatial concentration (asymmetry among regions) in the high-tech sectors almost three times higher than for the manufacturing sectors as a whole. In an analogous way, the first four largest provinces account for about 70% of all patenting activities in the high-tech sectors and only around 52% in all manufacturing sectors (see Table 2). Also in this case, the Herfindahl equivalent number shows that the spatial concentration of patenting activities in the high-tech sectors is about two times higher than that registered in all manufacturing sectors³.

In the second place, the analysis of the above indicators also shows the existence of considerable differences across high-tech sectors in the patterns of spatial concentration of trade and innovative activities. By and large, we can distinguish among at least three groups of sectors that differ according to the values taken by the three indicators used here.

A first group of sectors comprises industrial automation, measurement and control instruments, and optical instruments, systems and apparatus. These sectors are characterised by relatively high degrees of spatial diffusion, both with respect to exports and innovative activities. The values of the three concentration indicators for these sectors are in fact around or below the average value recorded for all high-tech sectors. Although we do not find any evidence of spatial concentration of innovative and trade activities, we cannot, however, reject completely the hypothesis that knowledge proximity matters for these sectors in mediating knowledge flows and spillovers. What we do observe from maps (not reported here) in these sectors is indeed a “localised” diffusion of productive, trade and innovative capabilities. In other terms, such capabilities, while being relatively diffused, are not scattered around the space, but they tend to remain within the borders of well defined sets of contiguous provinces.

A second group of sectors can be identified including office equipment, consumer electronics, electronic components and pharmaceuticals. Among the high-tech sectors, these sectors exhibit the highest levels of spatial concentration, both with respect to export and, especially, innovative activities. For this kind of sectors the benefits accruing from being spatially clustered outweigh any possible diseconomies of agglomeration, thus leading to the geographical concentration of innovative and export activities.

A third group of sectors comprises plastics, elastomers and fibres, and fine chemicals and specialties. Rather interestingly, these two sectors present a peculiar combination of high levels of spatial concentration of innovative activities and relatively high degrees of spatial diffusion of

³ It is also rather interesting to note that the spatial concentration of innovations resulting from the localisation of patenting firms is considerably higher than that emerging from the localisation of inventors.

exports. A possible explanation for this spatial pattern is that, while innovative activities are concentrated close to the headquarters and the R&D labs of the major chemical firms operating in Italy, exports are spread across many regions where establishments and units carrying out productive activities are located.

Finally, a rather peculiar case is represented by the electromedical instruments sector. Here, we observe rather high levels of spatial diffusion of innovative activities, on the one hand, and quite high degrees of spatial concentration of exports, on the other hand. Among the possible causes for this kind of spatial pattern, the importance of institutions, like University hospitals and public research institutes, in stimulating and organising the innovative process plays a fundamental role.

Also from a dynamic perspective, one finds rather strong differences across high-tech sectors in the evolution of the spatial concentration of exports and innovations over time.

With respect to exports, a quite clear trend of spatial diffusion characterises three sectors: pharmaceuticals, plastics, elastomers and fibres, and fine chemicals and specialties. Less uniform is the trend that characterises two electronic sectors (office machines and electronic components), while a fundamental stability in the spatial concentration of exports characterises the consumer electronics sector. The spatial concentration of exports increases rather sharply instead in three sectors (industrial automation, measurement and control instruments, and optical instruments, systems and apparatus), which are also the ones showing the highest levels of spatial diffusion of exports in absolute terms.

With regard to the patenting activity, most high-tech sectors show a tendency towards a spatial diffusion of innovative capabilities. The trend is stronger in five sectors: industrial automation, plastics, elastomers and fibres, electromedical instruments, measurement and control instruments and optical instruments, systems and apparatus. Moreover, this result holds both with reference to the localisation of patenting firms and to the localisation of inventors (see Tables 2 and 3). An increase in the spatial concentration of innovative activities can be observed only in one high tech sector, namely electronic components. For the remaining sectors, pharmaceuticals and fine chemicals and specialties show rather stable values of spatial concentration of innovative activities, whereas no clear trend emerges with reference to the electronic sectors.

4. Model framework

In order to provide a better description of the spatial structure of our data, we have carried out a cluster analysis based on the profiles of trade specialisation of the 95 NUT3 Italian provinces. For each of the 95 provinces and each of the 11 high technology sectors, we have first calculated the revealed trade comparative advantage (RCA) index, defined as follows:

$$(1) \quad RTA_j^i = \frac{E_j^i / E_j^{EU}}{E_M^i / E_M^{EU}}$$

where:

E_j^i = value of 1995 exports of province i in the high-tech sector j

E_j^{EU} = value of 1995 exports of European Union (15) in the high-tech sector j

E_M^i = value of 1995 exports of province i in all manufacturing sectors

E_M^{EU} = value of 1995 exports of European Union (15) in all manufacturing sectors

An RCA of more than 1 therefore shows a province's relative specialisation (i.e. strength) in a given high technology sector, whereas an RCA of less than 1 indicates its relative weakness. The RCA index has been standardised to take values comprised between -1 and 1 , where a positive (negative) value indicates relative specialisation (despecialisation) of a province in a given high technology sector⁴.

Using provinces' RCAs in the 11 high technology sectors as variables, we have applied the *SAS Fastclus* clustering procedure in order to obtain groups of provinces sharing similar profiles of trade specialisation in high technology sectors. This procedure is sensibly more flexible for non-spherical clusters, thus controlling for possible "chain" grouping of contiguous provinces. Each group of provinces with similar profiles of specialisation is summarised in its "mean profile" bearing "average" scores in trade sectoral specialisation. Map 1 reports the results of this cluster analysis. What an examination of the map suggests is that trade comparative advantages are not only localised into small sets of provinces, but they also spread over neighbouring provinces. In other words, there is evidence of spatial clusters of provinces having similar profiles of trade comparative advantages. In this respect, it is interesting to note the existence of clusters of adjacent provinces in the north-west and the north-east part of the country specialised in the industrial automation and measurement and control instruments

⁴ The standardised RCA index is defined as: $RTAS_j^i = \frac{RTA_j^i - 1}{RTA_j^i + 1}$.

sectors. A fairly more scattered spatial pattern of trade specialisation characterises instead the fine chemicals and specialties sectors. Provinces with a profile of specialisation in this sector are more evenly distributed throughout the whole country, but they all have quite low export shares. No significant evidence is found, moreover, of clusters of specialised adjacent provinces. Finally, only few and mostly isolated provinces appear to be specialised in the electronics sectors.

The major objective of this paper is to provide an empirical evaluation of the impact of localised knowledge spillovers on the trade comparative advantages of provinces. To this purpose, we assess a *global* or *whole-map* statistical relationship between trade and innovative competitiveness of provinces. More particularly, we assume that the trade performance of any given province in a high technology sector is a function of its innovative strength in the same sector and of the innovative strength of adjacent provinces in the same sector. This latter variable captures the impact that innovative activities in neighbouring areas have on trade performance of a given province, i.e. localised knowledge spillovers. The relationship to test is formally expressed as follows:

$$(2) \quad {}_jY_{it} = \alpha + \beta {}_jX_{it} + \gamma W {}_jX_{it} + \varepsilon_{it}$$

$i = 1 \dots 95$

$j = 1 \dots 11$

$t = 1991, 1995$ for exports and $t = 1989-91, 1993-95$ for patents

Y_{it} = share of exports of province i in high-tech sector j in year t

X_{it} = share of patents of province i in high-tech sector j in year t

$W = 95 \times 95$ connectivity matrix.

The 95×95 connectivity matrix W is built as follows. For each pair of provinces i and j , the cell of the matrix w_{ij} takes value 1 if the two provinces share a boundary and 0 otherwise. In what follows, however, we will adopt a connectivity matrix W with row sums standardised to unity. A striking feature of the global spatial distribution of patent shares in all high technology sectors is indeed their concentration in a low number of provinces. Using a standardised W matrix allows us to take into account the effect of innovative activities in adjacent provinces, while smoothing skewness at the local level. Moreover, in testing the relationship between exports and patents, it also allows us to smooth possible biases due to the statistical attribution of export flows at the local level (see above).

The spatial interaction-model specified above is basically consistent with the theoretical framework discussed for innovation and trade. On the other hand, alternative spatial error-model specifications do not seem to be relevant as the residuals from a preliminary fit of the model:

$${}_jY_{it} = \alpha + \beta {}_jX_{it} + \varepsilon_{it}$$

point out the absence of any significant lagged correlation based on the matrix W introduced.

Another econometric issue requiring attention concerns the possible heteroskedasticity of disturbances. Using various tests for heteroskedasticity, we could not always accept the null hypothesis of homoskedasticity⁵. In the following regressions, statistical significance of estimated coefficients will consequently be evaluated using adjusted t-values according to the heteroskedasticity-consistent covariance estimator as suggested by White (1980). This adjustment allows to take into account the possible heteroskedasticity of residuals from the estimated equation thus avoiding consequences on the reliability of estimated variances of parameters and therefore on the validity of hypotheses tests.

5. Empirical results

Before testing the regression model specified in equation (2), we have checked for the presence of spatial outliers. In models such as (2) it is well known that estimates of both the regression and spatial parameters are sensitive to the presence of outliers and to spatial clusters of outliers. The problem, however, is not so clear cut, neither the solution for it is generally straightforward (Haining, 1990).

Because of the extreme spatial concentration of our data and the scattered pattern of the spatial distribution, the detection of outliers is restricted to few economically important cases. In Italy, the province of Milan is where most economic activities (particularly in the high technology industries) are concentrated. This is apparently true for both exports and patents and this certainly affects the estimates of the regression model. On the other hand, the area in itself is likely to be very influential to the surrounding provinces, being therefore not a proper outlier. Thus, we choose to evaluate the equation (2) *without* this particular observation, but *including* relevant spatial information by deleting it from the regressor WX after multiplication⁶.

Table 4 reports the results of the OLS estimates of (2) for the 11 high technology sectors in 1991 and 1995, respectively.

⁵ In particular, the residuals from the estimated model are highly correlated with the size of provinces, as measured by the share of productive establishments located in the province.

⁶ Following the same approach, the observation of Naples has been deleted in 1995 from the regression for optical instruments because of the presence of an extreme value in the export share.

The parameter of the local patent share X is statistically significant and it presents a positive sign in most high-technology sectors in both periods of time. In broad terms, this results indicates the existence of a rather strong link between trade performance and innovative capabilities of any given province.

With respect to the variable capturing the impact of localised technological spillovers- i.e. the “spatially lagged” patent share WX - the parameter in regression estimates for 1991 is statistically significant in five high technology sectors: fine chemicals, office machines, electronic components, aerospace, and optical instruments. In regression estimates for 1995, the same parameter is statistically significant in four high technology sectors: fine chemicals, industrial automation, electronic components, and measurement and control instruments⁷.

However, it is very important to note that in those cases where the coefficient of WX is statistically significant, its sign differs between sectors. In particular, the parameter of WX takes a *positive* sign in four high-tech sectors: fine chemicals, industrial automation, measurement and control instruments, and optical instruments. This result indicates therefore that in these sectors *localised technological spillovers* have a positive impact on the trade performance of provinces; the innovative activities carried out in adjacent provinces have a positive impact on the trade performance of a given province. The strength of such effect seems to be particularly strong in the fine chemicals and industrial automation sectors. The parameter of WX takes instead a negative sign in the office machines, electronic components, and aerospace sectors. This result can be interpreted as a consequence of the highly localised and sparse distribution of trade and innovative activities in these sectors. Under such circumstances, the innovative activity carried out in neighbouring provinces does not have any impact on the trade performance of a given area.

6. Concluding remarks

In this paper, we have provided an empirical assessment of the relationship between localised technological spillovers and regional trade performance in high technology industries in Italy. In broad terms, the empirical evidence seems to support the hypothesis that the innovative activities carried out in adjacent provinces have an impact on the trade performance of any given province. The results also indicate that the strength of such relationship differs across high technology sectors. The impact of localised technological externalities seems to be more important in the industrial automation and instruments sectors. In these sectors, technological capabilities, while being relatively diffused across a quite large number of provinces, are not

⁷ In the regression for the measurement and control instruments sector, we have deleted, in addition to Milan, two outlier observations (the provinces of Rome and Turin) that strongly affect the estimates.

scattered around the space, but they tend to remain within the borders of well defined sets of contiguous provinces. This type of result also emerges with respect to the fine chemicals sector. In the electronics sectors, on the contrary, there is no evidence of any positive effect of localised technological spillovers. In these latter sectors, trade and innovative activities are highly polarised into one or two rather isolated provinces. In these cases, innovative activities carried out in neighbouring provinces do not affect the trade performance of a given area.

Our analysis suggests at least two directions of future research. On the one hand, more attention should be paid to exploring the role of sector-specific variables and, in particular, the sectoral organisation of innovative activities, in terms of concentration of innovators, size of innovators, rates of innovative natality and mortality, and so on. Moreover, the analysis should explicitly include other relevant economic variables, like inward and outward direct investments, size of firms and the like. On the other hand, the robustness of the results should be tested by exploring different specifications of the connectivity matrix W used here to model the effects of localised knowledge spillovers.

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Table 1 – Spatial concentration of exports, 95 provinces

Sectors	C1				C4				HEN			
	1988	1991	1993	1995	1988	1991	1993	1995	1988	1991	1993	1995
Pharmaceuticals	48.5	46.2	39.0	35.8	70.7	71.7	67.9	65.5	3.8	4.1	5.3	5.8
Plastics, elastomers and fibres	25.2	26.6	25.8	24.8	50.5	50.1	48.6	46.6	10.3	9.8	10.5	11.4
Fine chemicals and specialties	34.2	35.0	28.4	31.4	56.8	49.6	50.5	55.0	6.8	7.3	9.2	7.9
Industrial automation	19.7	13.9	19.9	20.2	58.0	51.6	54.2	56.2	9.8	11.3	10.7	9.8
Office machines	36.7	41.6	33.3	34.4	91.7	91.3	87.5	89.5	3.5	3.5	4.1	3.9
Consumer electronics	45.2	45.9	50.1	50.0	67.8	69.8	67.7	68.6	4.2	4.0	3.7	3.7
Electromedical instruments	61.0	57.8	58.0	52.5	78.8	77.0	82.0	78.0	2.6	2.8	2.8	3.3
Electronic components	55.7	59.3	56.3	52.2	87.3	89.6	86.6	84.8	2.8	2.4	2.8	3.1
Aerospace	25.3	22.6	24.4	20.6	74.6	68.5	65.2	68.2	6.1	7.2	7.1	7.1
Measurement and control instruments	31.4	30.5	33.8	33.6	60.9	59.6	57.0	58.2	7.3	7.5	6.9	6.8
Optical instruments, systems and apparatus	23.5	22.6	18.1	19.9	46.7	48.1	39.2	55.6	10.9	11.6	15.4	9.4
High-tech sectors	32.9	34.2	33.6	33.8	60.9	61.4	59.9	57.0	6.9	6.7	6.9	7.0
All sectors	17.7	17.9	16.5	15.0	35.7	34.5	32.3	35.5	18.2	18.8	20.8	20.7

Table 2 - Spatial concentrations of innovations, 95 provinces (location of patenting firms)

Sectors	C1			C4			HEN		
	1983-'85	1989-'91	1993-'95	1983-'85	1989-'91	1993-'95	1983-'85	1989-'91	1993-'95
Pharmaceuticals	60.9	54.6	47.6	84.4	77.3	78.0	2.5	3.1	3.6
Plastics, elastomers and fibres	93.5	83.3	67.3	100.0	95.1	93.8	1.1	1.4	2.0
Fine chemicals and specialties	65.9	58.1	50.7	86.4	83.9	81.2	2.2	2.6	3.6
Industrial automation	31.5	22.4	20.5	70.4	57.7	55.1	5.3	8.2	9.9
Office machines	40.0	85.2	68.1	91.4	93.8	88.0	3.0	1.4	2.1
Consumer electronics	47.3	56.7	56.0	87.8	89.2	86.4	3.4	2.7	2.9
Electromedical instruments	37.5	40.5	16.7	87.5	64.9	55.6	4.0	5.1	9.7
Electronic components	29.4	70.2	56.3	79.4	88.6	91.1	5.2	2.0	2.4
Aerospace	66.7	62.5	100.0	100.0	100.0	100.0	1.8	2.1	1.0
Measurement and control instruments	36.0	37.5	30.3	74.2	70.5	60.7	5.0	5.3	7.1
Optical instruments, systems and apparatus	23.8	41.2	28.9	81.0	70.6	66.7	5.6	4.7	6.5
High-tech sectors	41.8	55.1	49.1	74.7	75.3	69.3	4.4	3.1	3.9
All sectors	29.6	31.2	32.9	55.4	52.1	52.3	7.8	8.2	7.7

Table 3 - Spatial concentration of innovations, 95 provinces (location of inventors)

Sectors	C1			C4			HEN		
	1983-'85	1989-'91	1993-'95	1983-'85	1989-'91	1993-'95	1983-'85	1989-'91	1993-'95
Pharmaceuticals	41.3	44.1	40.9	67.5	65.0	68.3	4.7	4.6	4.8
Plastics, elastomers and fibres	44.4	29.5	26.9	77.1	62.4	59.5	4.1	7.5	8.0
Fine chemicals and specialties	23.2	43.2	32.3	61.7	63.5	60.7	7.8	4.8	7.0
Industrial automation	28.2	21.6	20.3	68.2	52.5	55.3	6.0	9.9	9.4
Office machines	37.2	57.3	40.3	82.1	77.3	67.9	4.1	2.9	5.1
Consumer electronics	44.4	34.2	29.4	78.4	77.6	57.9	4.0	5.0	8.1
Electromedical instruments	20.0	34.4	16.4	64.0	58.0	41.7	8.3	6.7	14.5
Electronic components	30.6	37.1	38.3	68.1	71.6	78.0	6.2	5.1	3.8
Aerospace	33.3	50.0	25.0	100.0	80.0	87.5	3.0	3.4	4.6
Measurement and control instruments	28.9	24.0	22.4	69.1	54.9	51.9	6.6	9.7	10.6
Optical instruments, systems and apparatus	20.8	32.2	18.1	72.9	54.6	54.5	6.7	7.5	10.3
High-tech sectors	28.5	34.3	30.3	60.9	55.7	49.7	7.7	7.0	8.8
All sectors	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

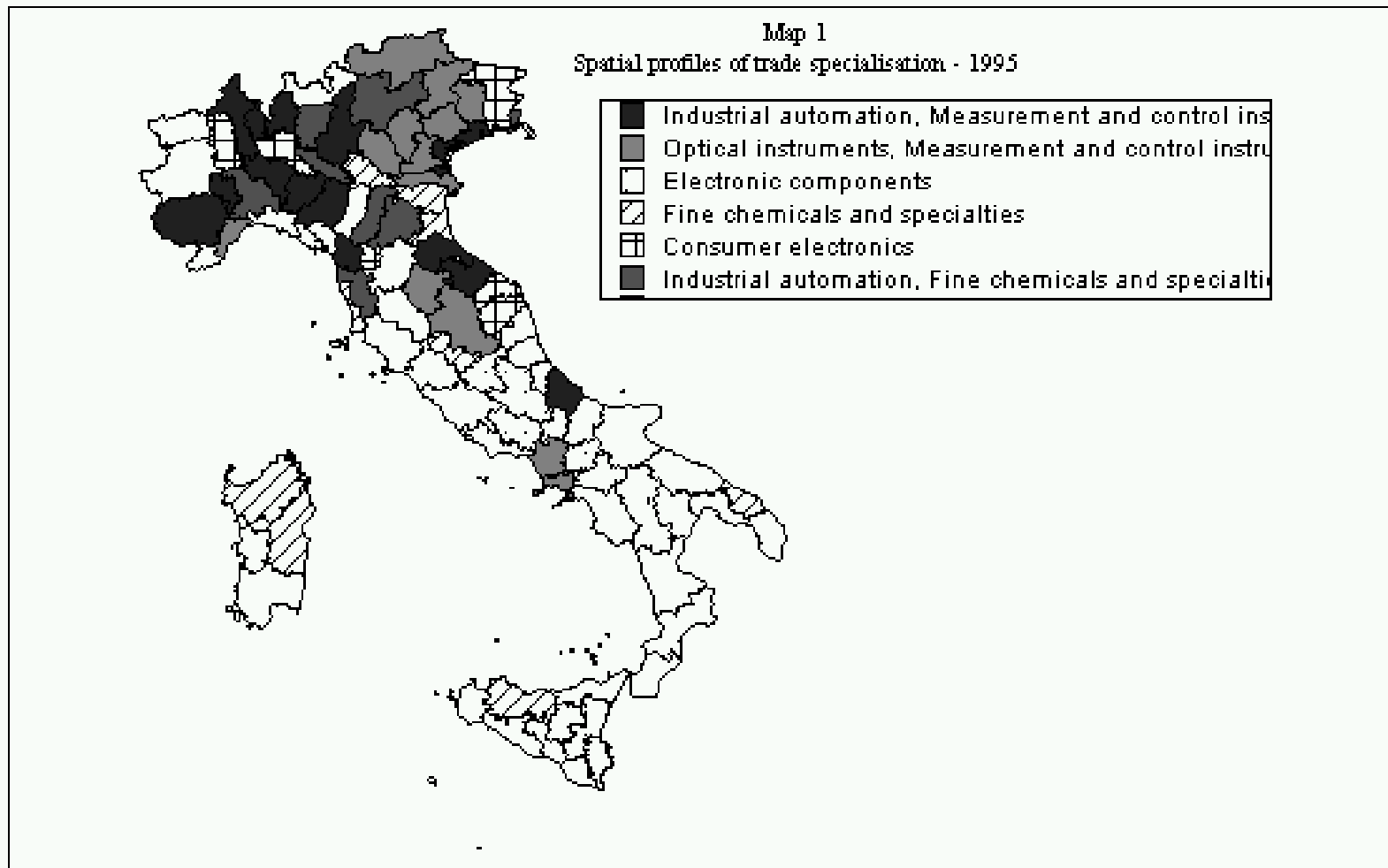


Table 4 – Regression estimates of the impact of localised knowledge spillovers (OLS)

<i>Sectors</i>	1991				1995			
	<i>Const</i>	<i>X</i>	<i>WX</i>	<i>Adj. R²</i>	<i>Const</i>	<i>X</i>	<i>WX</i>	<i>Adj. R²</i>
Pharmaceuticals	0.23* (0.12)	0.51*** (0.12)	0.007 (0.06)	0.18	0.23** (0.09)	0.43*** (0.04)	0.14 (0.12)	0.22
Plastics, elastomers and fibres	0.46*** (0.13)	0.40** (0.17)	-0.002 (0.07)	0.24	0.37*** (0.09)	0.38*** (0.06)	0.12 (0.08)	0.46
Fine chemicals and specialties	0.32*** (0.10)	0.22*** (0.08)	0.12*** (0.04)	0.28	0.36* (0.14)	0.32*** (0.12)	0.12* (0.07)	0.25
Industrial automation	0.11 (0.12)	0.56*** (0.07)	0.24 (0.16)	0.38	-0.13 (0.18)	0.60*** (0.11)	0.38* (0.22)	0.49
Office machines	-0.01 (0.19)	2.13*** (0.79)	-0.19* (0.11)	0.55	0.28 (0.26)	1.18 (0.86)	-0.25 (0.20)	0.26
Consumer electronics	0.35*** (0.11)	0.28 (0.25)	-0.01 (0.05)	0.17	0.32*** (0.09)	0.43** (0.18)	-0.09 (0.06)	0.35
Electromedical instruments	0.07 (0.06)	0.26** (0.11)	0.12 (0.09)	0.16	0.07 (0.13)	0.34*** (0.08)	0.09 (0.14)	0.20
Electronic components	0.38 (0.28)	0.16*** (0.04)	-0.05*** (0.01)	0.00	0.45* (0.24)	0.16*** (0.02)	-0.03*** (0.01)	0.04
Aerospace	0.73*** (0.33)	0.37*** (0.06)	-0.15** (0.07)	0.30	0.83** (0.38)	0.23** (0.15)	-0.08 (0.06)	0.07
Measurement and control instruments	0.01 (0.07)	0.61*** (0.21)	0.10 (0.06)	0.46	0.02 (0.06)	0.66*** (0.08)	0.08* (0.04)	0.63
Optical instruments, systems and apparatus	0.30** (0.14)	0.39*** (0.11)	0.14* (0.07)	0.16	0.15 (0.14)	0.15* (0.08)	0.30 (0.20)	0.20

Notes: in parentheses heteroskedasticity-robust standard errors.

* statistically significant at 0.10 level; ** statistically significant at 0.05 level; *** statistically significant at 0.01 level

