Proximity and Innovation in Italian SMEs

Morone, Piergiuseppe and Petraglia, Carmelo and Testa, Giuseppina

Università degli Studi di Foggia, Università degli Studi di Napoli, Federico II, Università degli Studi di Foggia

5 December 2008

Proximity and Innovation in Italian SMEs*

Piergiuseppe Morone♦[a], *Carmelo Petraglia*[b] *and Giuseppina Testa*[c]

This version 05.12.2008

Abstract: In this paper we assess the relevance of both knowledge creation and diffusion processes in affecting Italian SMEs' propensity to innovate. In doing so a knowledge production function (KPF) is estimated for a representative sample of small and medium manufacturing firms over the period 1998-2003. To account for endogeneity of R&D effort in the KPF, we estimate a Heckman selection model on R&D decisions and obtain two main results. First, we do not find the probability of being engaged in intramural R&D activities to be significantly related to firm size. Second, for those firms engaged in R&D activities, the intensity of R&D effort increases with firm size. Then, the KPF is estimated for three different samples of firms using a standard probit where the probability that SMEs will innovate depends upon intramural R&D effort, regional and industrial spillovers and a vector of interaction and control variables. The main results obtained from this second set of regressions are the following: first, we find the probability to innovate to be positively related to sectoral spillovers, the magnitude of such impact being decreasing in firms' size. Second, knowledge diffusion via geographical proximity enhances the probability of the recipient firm to innovate only if it has an appropriate endowment of human capital.

JEL classification: O3, L6, C25
Keywords: Innovation, knowledge, spillovers, firm size

---

* The authors are grateful to Marco Vivarelli for helpful comments provided on an earlier version of the paper and to Nick von Tunzelmann for precious suggestions and comments. The authors also thanks Cesare Imbriani for the helpful discussion provided in different stages of the work. Capitalia data and helpful advice from Attilio Pasetto (Area Studi Capitalia) are gratefully acknowledged. The usual disclaimers apply.

♦ Corresponding author: Piergiuseppe Morone (p.morone@gmail.com).

[a] Università degli Studi di Foggia, Largo Papa Giovanni Paolo II, 71100 – Foggia, Italy; email: p.morone@gmail.com

[b] Università degli Studi di Napoli "Federico II", Dipartimento di Economia, Via Cintia, Complesso M. S. Angelo – 80126 – Napoli – Italy; e-mail: carmelo.petraglia@unina.it

[c] School of Economics, Mathematics and Statistics, Birkbeck, University of London, Malet Street, London WC1E 7HX: gtesta@econ.bbk.ac.uk

1. Introduction

The sluggish performance of the Italian economy since the second half of the 1990s has been at the heart of a wide-ranging debate among both scholars and policy makers. Particular attention has been given to the undergoing crisis of competitiveness of Italian producers reflected in the declining share of Italian firms in world trade in the last decade. These trends call for explanations which must take into consideration both the peculiar characteristics of the Italian model of specialization (i.e. the so-called *made in Italy* sector), as well as the specific characteristics of individual firms (e.g. size, attitude to innovate, knowledge deepening, etc.). In this paper we do not aim to provide an exhaustive analysis on the ongoing debate on Italian firms' competitiveness (or the lack of it). However, bearing in mind that in high-income knowledge-based economies innovation is a crucial asset for firms' long-term competitiveness, we aim at contributing to the debate by providing some new insights into the determinants of innovating behaviour. We shall do so by placing our attention on both internal and external (to the firm) sources of knowledge creation and diffusion as crucial inputs of innovation. Specifically, we shall investigate two factors which potentially shape innovating patterns: the presence of knowledge diffusion across firms operating in the same sector (via industrial proximity) and/or across firms located in the same region (via geographical proximity).

The structure of the paper is as follows: section 2 provides a motivation to this study; section 3 sets out the empirical model; section 4 introduces our dataset and presents empirical results; and, finally, section 5 concludes.

2. Motivation and related literature

Several scholars link the above-mentioned loss of competitiveness of Italian firms to the structural characteristics of the national manufacturing system (see, for instance, Faini and Sapir, 2005). In particular, they claim that the Italian specialization model – mainly oriented towards mature and low-tech sectors – is nowadays obsolescent and inadequate to cope with globalization (not shifting production towards high-tech sectors, as other countries do).

Such a view, however, seems to be only partially confirmed by the empirical evidence. For instance, it has been observed (Bank of Italy, 2005: 30) that the fall in the Italian share of world exports observed over the period 1996-2002 is due mainly to a loss of competitiveness of Italian products – such as changes in prices, quality and other factors related to export competitiveness – while the sectoral and geographical specialization of Italian exports and the adaptation of this structure to the evolution of world markets were found to be correlated with this fall only to a smaller extent.[1] Similarly, it was found (ICE, 2007: 185) that the fall in the Italian share of world exports during a longer time span – 1997-2006 – is due mainly to changes in relative prices and other factors of competitive success rather than to the degree of conformity in the specialization of exports to the changes in the composition of demand of the destination markets.

A lesson that can be learnt from the above-mentioned empirical evidence is that factors affecting the degree of competitiveness of Italian products in the global market are likely to be independent of the national specialization model. As it is not possible to identify *a priori* the 'winning' sectors, and consequently encourage the dismissal of traditional production in favour of high-tech ones (Barba Navaretti et al., 2007: 2), more emphasis should be placed on firm-specific factors (regardless of their sector of activity) in order to understand the difficulties faced by Italian producers in competing in international markets.

As is well known, it is becoming increasingly relevant for firms located in wealthier countries to base their competitive advantage on the knowledge content of their products in order to overcome the competitive advance of emerging countries which, on the other hand, can rely on much cheaper labour cost (see, for instance, Pinch et al., 2003;

[1] In a publication by the Bank of Italy (2005), a constant-market-share analysis is implemented to break down the overall change in the Italian market share over the period 1996-2002 into three components: the sectoral and geographical specialization of exports in the initial period (structure effect), the adaptation of this structure to the evolution of world markets (adaptation effect) and a residual component given by the variations in market shares in each sector and country deriving from changes in prices, quality and other factors of export competitiveness (competitiveness effect). Simulations are implemented using data on 27 sectors and 21 OECD markets, accounting for 70% of total Italian exports. Two thirds of the loss of share in the reference market is found to be due to the competitiveness effect, while smaller losses are directly attributed to the sectoral and geographical specialization of Italian exports and to the difficulties encountered by Italian producers in reorienting their specialization towards more dynamic product segments and markets.

Forsman and Solitander, 2003). Such a 'knowledge-based' model of production requires that a firm is highly committed to innovation activities resulting from well-behaving processes of both knowledge creation and diffusion. In fact, intramural research activities as well as knowledge spillovers are both relevant factors that can potentially affect firms' innovative propensity (for seminal contributions, see Griliches, 1991, and Jaffe, 1986).

As for the case of Italy, given the major role played by small and medium-sized enterprises (SMEs) in shaping its economic system, it can be argued that this structure might represent an obstacle to innovating activities. Indeed, since the seminal contribution by Schumpeter (1942), the link between firm size and innovation has been at the heart of the economic debate, with the positive correlation between firm size and commitment to formal R&D activities being a common finding in empirical works.

In point of fact, Italian business R&D intensity is weak compared to other advanced economies, where large companies play a stronger role. However, regardless of the reluctance of Italian firms to commit themselves to R&D, "the country's performance tops the EU average for the sales of new-to-market products and comes close to the average for new-to-firm-products. The satisfactory performance for sales from new-to-market innovation could reflect innovative processes specific to firms, difficult to classify and register in official statistics. This is the case of design innovation, one of the strengths characterising some of the most successful 'made in Italy' products (e.g. high fashion, luxury goods)" (Technopolis Group, 2006: 4).

As the empirical literature on the Italian case shows, SMEs can contribute significantly to innovative output (see amongst others Piergiovanni et al., 1997; Morone and Testa, 2008). One commonly agreed-on explanation for such evidence is that SMEs can potentially benefit from knowledge spilled-over by other firms or institutions.

Using a representative sample of Italian SMEs observed over the period 1998-2003, we will assess the relevance of both knowledge creation and diffusion processes in driving Italian SMEs' propensity to innovate.

3. Empirical strategy

Our main interest is to assess the impact of both internal and external knowledge inputs on SMEs' innovation activities, by estimating a KPF augmented with knowledge spillovers.

Following Crépon et al. (1998), Griffith et al. (2006) and Morone et al. (2007), we observe that the estimation of any knowledge production function is possibly subject to endogeneity. This occurs for two main reasons: first, intramural R&D expenditure may be correlated with unobservable factors because firms that expect to be able to innovate are those that might be more likely to be engaged in R&D. Second, since firms can in principle undertake some R&D activities without reporting R&D investment, internal R&D effort may be measured with error.

In order to tackle endogeneity, we first run a Heckman selection model on R&D decisions, which allows us to obtain internal R&D investment conditioned on the decision to undertake R&D activities. In doing so, we account for endogeneity and obtain our measure of the internal knowledge input to be included in the KPF.

As for possible external (to the firm) sources of knowledge, we assume that knowledge diffusion across firms might occur via either geographical or industrial proximity. That is to say, a given firm can in principle exploit innovative inputs used by other firms by means of spillovers occurring within both the 'industrial space' populated by firms operating in its same sector and the 'geographical space' where it is located.[2] Accordingly, we measure knowledge spillovers as follows:

$$W_{is} = \sum_{j \neq i} \hat{R}_{js} \tag{1}$$

where W_{is} is total knowledge available to firm i in space $s=[x, y]$ and is obtained by aggregating R&D predicted values delivered by the Heckman selection model for any

[2] We use the 14 sectors provided in our sample as a framework for calculating the sectoral spillover variable (these are: Food & beverage, Clothing, Footwear & leather, Wood & furniture, Paper, Fuel, Chemical products, Plastic products, Mineral products, Metal products, Mechanical products, Electrical equipment including optical instruments, Motor Vehicle and Other sectors). Regional spillovers are calculated using the 19 Italian Regions (Valle D'Aosta and Piemonte are counted as one).

other firm j in the same space.[3] Note that, as SMEs are likely to benefit from knowledge created by other firms regardless of their size, our measure of spillovers uses information on the R&D effort of our full sample of Italian manufacturing firms, including large firms. This is because we believe knowledge might spill over from any firm operating in the geographical/industrial space of reference for a given SME.

Once having obtained both internal and external sources of knowledge, we define the following KPF:

$$I_i = \hat{R}_i^{\alpha} W_{ix}^{\beta} W_{iy}^{\eta} C_i^{\gamma} K_i^{\lambda} (H_i W_{ixy})^{\phi} \tag{2}$$

where i indexes firms, x industries and y regions. I_i represents innovative activities (product innovation and/or process innovation) reported by firm i and $\hat{R}_i$ its internal R&D effort. W_{ix} measures aggregate industry-specific knowledge created by firms operating in the same sector x as firm i, while W_{iy} is aggregate geographical-specific knowledge created by other firms located in the same region y. K_i is the physical capital of firm i, C_i a vector of control variables which capture heterogeneity across firms and H_i a measure of the firm's human capital. Using lower-case letters to denote natural logarithms, we obtain the KPF to be estimated:

$$i_i = \hat{r}_i'\alpha + w_{ix}'\beta + w_{iy}'\eta + C_i'\gamma + k_i'\lambda + H_i w_{ixy}{}'\phi + \varepsilon_i \tag{3}$$

As we are interested in singling out the size effects on knowledge absorption and innovation, we estimate Eq. (3) for three samples of firms: small and medium firms (less than or equal to 250 employees); medium-small and small firms (less than or equal to 100 employees); and small firms (less than or equal to 50 employees).[4]

[3] Eq. (1) assumes a unitary absorption capacity across firms. Our results will show that the ability of a firm to capture available external knowledge is increasing in its internal endowment of human capital.

[4] Note that we subsequently decided to reduce the sample from small and medium to medium-small and small firms rather than considering them separately, in order not to incur problems associated with the sample size.

We are aware that the innovating behaviour of a firm is potentially influenced by proximity to other firms, the sign of such an influence being not easy to disentangle though. Hence, we do not formulate any expectation on the sign for the coefficients of variables associated with knowledge spillovers. As a recent survey on the topic (Boschma, 2005) summarizes, proximity between two economic agents – in any of its organisational, technological, industrial, cultural, geographical, cognitive, institutional dimensions – can both enhance or hamper knowledge exchange.

For example, industrial proximity may have positive impact on innovation because firms operating in the same industry may share the same knowledge base and expertise and thus may learn from each other. According to Boschma and Lambooy (1999), in fact, firms search in close proximity to their existing knowledge base in order to communicate, understand and process knowledge successfully. However, using a different argument, Cantwell and Santangelo (2002) argue against the positive sign of industrial proximity. They maintain that as firms operating in the same or strongly overlapping technological fields may compete, they may be encouraged to locate their knowledge research activities in different places. Also the sign of geographical spillovers is doubtful. A large body of literature (see, among many others, Howells, 2002) claims that agents that are spatially concentrated benefit from knowledge externalities because short distances favour information contact and facilitate the exchange of tacit knowledge. However, it has also been noted that the exchange of knowledge in the geographical space requires strong social ties (resulting, for example, from past collaborative links between firms) in the absence of which geographical proximity does not exert any effect upon knowledge diffusion (see, for instance, Singh, 2003; Morone et al., 2006).

4. Data and Results

The data were retrieved from the last two waves (8^{th} and 9^{th}) of the Capitalia survey on Italian manufacturing firms with more than 10 employees, covering the periods 1998-2000 and 2001-2003 respectively (Capitalia, 2002 and 2005). In order to increase the time span of our analysis, we use the balanced panel of firms obtained in Morone et al.

(2007) by merging the 8th and 9th waves of the survey.[5] Table 1 reports descriptive statistics on firms' intramural R&D effort and innovative behaviour. The share of firms reporting R&D activities increases substantially when moving from the smallest size to larger categories. This is in line with our expectations as it shows that small firms (i.e. those with less than 51 employees) are less keen on doing formal R&D. Interestingly, a larger share of firms with 51 to 100 employees perform R&D when compared with those in the following size category (i.e. 101 to 250). R&D intensity increases exponentially with firms' size: it almost triples in moving from the first to the second category, nearly doubles in moving to the third category and increases nearly sixfold for large firms (i.e. more than 250 employees).

Table 1: Intramural R&D and Innovative Behaviour in the sample

	Firms with intramural R&D, 1998-2000		**R&D intensity in 2000, thousand euros***		**Innovative behaviour, 2001-2003****	
Firm size (employees)	Obs.	%	Mean	s.d.	Obs.	%
Between 10 and 50	241	29.18	73.458	94.001	428	51.38
Between 51 and 100	88	60.69	186.127	286.415	99	67.81
Between 101 and 250	55	57.89	378.137	458.781	69	71.13
More than 250	69	74.19	2,207.288	4,363.157	76	88.37

*R&D intensity is total expenditure on research and development (R&D) activities reported by the firms deflated by the output price.
**Innovative behaviour is based on firms' answer to the question "Have new product and/or process innovations been introduced over the period 2001-2003?"

When we look at innovation behaviour we can observe again how it is constantly correlated with firms' size. However, we can note now that there is a smooth transition from the smallest size to larger categories. This finding confirms what was discussed in section 2 – i.e. that small firms display innovation behaviours which cannot be explained from looking solely at formal engagement in R&D. This reinforces our hypothesis that spillover effects might actually play a key role in shaping innovation behaviour of small firms.

[5] The adopted merging procedure is described in detail in Morone et al. (2007).

Before presenting our empirical findings, a few words must be said on the innovation measure used in our investigation. As put by Kuznets (1962), the greatest obstacle to understanding the economic role of technological change is the scholars' inability to adequately measure innovation. Several measures have been proposed so far in the innovation literature.[6] In our study we use a dummy variable based on the answer provided to the following question: "Have new product and/or process innovations been introduced over the period 2001-2003?". Such measure presents both advantages and disadvantages. The main advantage is that, in principle, it should capture any innovation introduced by any firm and, hence, should not be affected by differences (such as those observed in the propensity to patent) which exist across sectors as well as across size classes. Nonetheless, our measure of innovation suffers from two shortcomings: first, it relies only on the perception of the firms' managers answering the questionnaire and second, it does not discriminate between innovations which are new to the firm or to the market.

Both of these problems refer to what Smith (2006) has labelled the "fundamental definitional issue" of what should be considered 'new': "[D]oes an innovation have to contain a basic new principle that has never been used in the world before, or does it only need to be new to a firm? Does an innovation have to incorporate a radically novel idea, or only an incremental change? In general, what kinds of novelty count as an innovation?" (2006: 149). We are aware that none of these issues are captured by our innovation measure.

In what follows we first describe results of the Heckman sample selection model, reporting evidence on the factors affecting both the choice of being engaged in and the

---

[6] Traditionally, measures of innovation outputs can be divided in two approaches: the 'object' approach and the 'subject' approach. Measures of the first approach range from patent counts and patent citations to new product announcements (recently, new data have been proposed; these are the Literature-based Innovation Output (LBIO) data which are compiled by screening specialist trade journals for new-product announcements - see van der Panne, 2007). The second approach focuses on the innovating agent and includes small-scale incremental changes. The most important example of the 'object' approach is the SPRU database, developed by the Science Policy Research Unit at the University of Sussex. The CIS (*Community Innovation Survey*), developed by the European Commission in a joint action between Eurostat and DG-Enterprise is one of the most comprehensive 'subject' oriented database which attempts to collect internationally comparable direct measures of innovation. For a comprehensive discussion on various measure of innovations see Smith, 2006.

intensity of the effort devoted to R&D activities. Then, we focus on the estimation of the KPF, analyzing the effects of knowledge spillovers on SMEs' propensity to innovate.

4.1 R&D choice and intensity

We estimate first a selection equation to observe whether a firm is engaged in R&D activities, and then an outcome equation to predict the intensity of R&D effort. In our specification, the decision to engage in R&D activities is regressed upon human capital endowment, location, age, size and export orientation of the firm and refers to the period 1998-2000.[7] In the outcome equation, R&D intensity is regressed upon size, location and human capital and refers to the year 2000, as we expect that R&D choice made over 1998-2000 affects the intensity of R&D investment at the end of the period.

Table 2 reports estimation results of the selection equation. Recall here that the dependent variable takes a value of 1 if the firm chooses to undertake R&D activity and 0 otherwise.

First, we can observe that the higher is the endowment of human capital, the greater the probability of doing R&D. Specifically, on average, by increasing the number of employees with university degrees by one, the probability of being involved in R&D increases by 1.4 percentage points. This result indicates that the differences in human capital endowment among firms do affect the firm's likelihood of undertaking R&D.

In addition, we investigate whether the presence in foreign markets makes firms more likely to perform R&D activities compared to those operating exclusively in domestic markets. It emerges that exports have a strong and positive effect on the probability of being engaged in R&D; specifically, being an exporter increases, *ceteris paribus*, the probability of doing R&D by 21 percentage points. This result is consistent with the finding that exporting makes firms more easily aware of foreign innovators' activities,

---

[7] Human capital endowment is measured as the number of employees with a higher education degree. As for the location of firms, we use a geographical dummy taking the value of 1 for firms located in the South of Italy and zero otherwise. The export orientation dummy is equal to 1 if the firm is involved in export activities and 0 otherwise.

whose outcomes can be assimilated in order to improve their position both in domestic and foreign markets (Barrios et al., 2003: 476).[8]

We also find that firms belonging to the science-based sector (according to the Pavitt taxonomy) have a higher probability of being engaged in R&D and that the responsiveness of a firm's choice to conduct R&D increases for younger firms.[9] Finally, we observe that none of the coefficients attached to size dummies is statistically significant at the 10% level (note that the base category is firms with more than 250 employees). This implies that the probability of being engaged in R&D activities is not affected by the size of the firm in a statistically significant way.

Table 2: R&D choice equation (estimation technique: Heckman)

Dependent variable: R&D enagagement (dummy variable referred to the period 1998-2000)				
	Coefficients		Marginal Effects	
	Estimates	P >| Z |	Estimates	P >| Z |
Human capital	0.037	0.048	0.014	0.051
South (1 if the firm is located in the South of Italy)	-0.043	0.770	-0.017	0.770
Micro size (1 if the firm has between 9 and 50 employees)	0.045	0.890	0.017	0.890
Small size (1 if the firm has between 51 and 100 employees	0.539	0.106	0.210	0.108
Medium size (1 if the firm has between 101 and 250 employees)	0.412	0.221	0.160	0.222
Export orientation (1 if the firm is involved in exporting activities)	0.566	0.001	0.211	0.000
Age of the firm	-0.007	0.049	-0.003	0.049
Science based sector (1 if the firm operates in HT and specialised sectors)	0.698	0.000	0.272	0.000
Constant	-0.883	0.020		

In the outcome equation (see Table 3) we find that R&D intensity is significantly and positively affected by human capital. The same holds for size: a higher level of R&D investment is associated with a larger firm size. Furthermore, being located in the South of Italy has a negative effect upon the amount of R&D investments.

Hence, we find that firm's size affects significantly R&D intensity but does not exert any effect on the probability of being engaged in R&D activities. This result is consistent with previous studies (Cohen, 1995; Freeman and Soete; 1997 among others) suggesting that R&D intensity is strongly related with firms' size when considering

[8]As we could have a potential endogeneity of exports, we regressed R&D engagement in 2003 on exports reported in the period 1998-2000 and found that the direction of the link between export and R&D is robust (results available upon request).

[9] The variable 'age of the firm' is defined as the years of activity of the firm.

solely those firms that perform R&D activities. In other words, although a vast majority of micro, small and medium sized firms declared not to be engaged in R&D activities, among those firms that did perform R&D, there is a significant relationship between size and R&D intensity.

Table 3: R&D amount equation (estimation technique: Heckman)

Dependent variable: R&D intensity (referred to year 2000)	Coefficients	
	Estimates	P >| Z |
Human capital	0.009	0.005
South (1 if the firm is located in the South of Italy)	-0.435	0.042
Micro size (1 if the firm has between 9 and 50 employees)	-1.463	0.000
Small size (1 if the firm has between 51 and 100 employees	-1.080	0.000
Medium size (1 if the firm has between 101 and 250 employees)	-0.566	0.085
Constant	13.08	0.000
Rho	-0.929	0.000
Wald test of indep. eqns	13.55	0.0002
Number of obs	553	
Censored obs	280	
Uncensored obs	273	

Finally, we note that the dependent variable is observed for 273 firms, while the remaining 280 firms in the sample do not report R&D. The *p-value* attached to the Rho estimate, which captures the correlation between the error terms of the R&D choice and the amount equations, suggests the presence of a selection bias, which supports the methodology adopted. This is also confirmed by the Wald test of independent equations as reported in Table 3.

4.2 The knowledge production function

Tables 4, 5 and 6 show the estimation results of the KPF for three categories of SMEs. Note here that the dependent variable (innovative output) is observed in the period 2001-2003, while regressors are observed over the previous three years (1998-2000) – specifically, intramural R&D effort, knowledge spillovers and human capital are observed in 2000, whereas physical capital refers to the whole period 1998-2000.[10]

[10] Throughout the three KPF regressions, some coefficients are only marginally significant at a 10% level.

As for ‘small and medium’ firms (see Table 4), the coefficient of the log of predicted R&D takes the expected sign and is statistically significant at 10% level: an increase of one unit in the log of R&D effort exerted in the year 2000 is associated with an increase of 22 percentage points in the probability of innovating in the period 2001-2003. Moreover, an increase of one unit in sectoral[11] knowledge spillovers is associated with an increase of around 10 percentage points in the probability of innovating. These results seem fairly intuitive: they suggest that performing R&D is likely to increase firms’ innovative activity and that knowledge circulates quite effectively at sectoral level. Further, a unit increase in the log of physical capital generates an increase of more than 4 percentage points in the probability of innovating.

Table 4: KPF for small and medium firms (estimation technique: probit)

Dependent variable: Innovation (dummy variable referred to the period 2001-2003)				
	Less than or equal to 250 employees			
	Probit coefficients		Marginal Effects	
	Estimates	P >| Z |	Estimates	P >| Z |
Log R&D (hat)	0.587	0.077	0.223	0.076
Log sectoral spillovers (hat)	0.263	0.037	0.100	0.037
Log regional spillovers (hat)	-0.170	0.057	-0.065	0.057
Human capital	-0.006	0.980	-0.002	0.980
HK- sectoral spillovers interaction	-0.025	0.511	-0.009	0.511
HK- regional spillovers interaction	0.031	0.068	0.012	0.067
Log of Physical Capital	0.113	0.014	0.043	0.014
Size (1 if the firm has more than 50 employees)	-0.283	0.241	-0.109	0.245
Constant	-8.454	0.016		
Number of obs	479			
Pseudo R2	0.054			

On the other hand, we find evidence of a negative and significant effect of regional knowledge spillovers on innovation.[12] Such an evidence seems to indicate that geographical proximity is harmful for effective knowledge transfers to take place across firms. Indeed, geographical proximity is neither a necessary nor a sufficiency condition for the transfer of knowledge to be effective. As Boshma (2005) points out, it is not

[11] Note here that we use the term “sectoral” as a synonymous of “industrial”.
[12] Note that the coefficient of regional knowledge spillovers does not change sign if aggregating knowledge at provincial level.

necessary because other forms of proximity can act as substitutes of geographical proximity.[13] According to our results, industrial proximity seems to play such a role. Furthermore, it is not sufficient because firms located in the same geographical space also need to be proximal from a cognitive point of view in order to effectively exchange knowledge. That is, they need to share a common knowledge base (see, for instance, Giuliani and Bell, 2005). Our results reflect this effect by depicting the positive role played by human capital which emerges form the positive and significant coefficient of the interaction term between regional spillovers and human capital endowment.
Another explanation of the negative relationship between geographical spillovers and innovation relies on the lack of strong social interactions among local firms. Recalling the wide literature that studies diffusion of information through social links (Rogers, 1995; Valente, 1995; Singh, 2003; Morone et al., 2006), in fact, it can be argued that the probability of reporting innovations is highly related to knowledge diffusion only if firms located in the same region are socially well connected. In light of this results, we may conclude that firms located in most of the Italian regions, lack a sufficiently tight social links.[14]

Table 5 refers to the KPF estimated for 'medium-small and small' firms, i.e. those with less than or equal to 100 employees. The marginal effect for the R&D expenditure measure is higher than that reported in Table 4. At the mean, increasing the R&D effort by one unit increases the probability of innovating by 37 percentage points. This finding implies that 'medium-small' firms extract higher value (in terms of innovative ability) from R&D investments.

In this case we also find that innovation is negatively affected by regional knowledge spillovers, with a marginal coefficient slightly higher than that reported in Table 4. Again a positive relationship between the probability of innovating and the interaction term between regional spillovers and human capital endowment is observed. In

[13] Boschma (2005) provides a comprehensive taxonomy of five forms of proximity (geographical, institutional, social, cognitive and organizational) studying the channels through which they either enhance or hamper knowledge transfers.
[14] Indeed this observation does not hold for all Italian regions, as local contexts strongly differ in terms of social capital endowments (for a survey on the relationship between local endowment and the rising of Italian industrial districts see Becattini, 1987).

accordance with the argument developed above, this result suggests that in order for regional spillovers to be effective in boosting innovations, firms are required to be endowed with an adequate level of human capital. Finally, the coefficient on the log of sectoral spillover is statistically significant and comparable in size to that reported in Table 4. This indicates that ‘medium-small and small’ firms also benefit from spillovers arising in the industrial space.

Note that in Tables 4 and 5 we have also included a size variable (set equal to one for those firms with more than 50 employees, and zero otherwise) which discriminates between medium-small and small firms; however, this variable is never statistically significant.

Table 5: KPF for medium-small and small firms (estimation technique: probit)

Dependent variable: Innovation (dummy variable referred to the period 2001-2003)				
	Less than or equal to 100 employees			
	Probit coefficients		Marginal Effects	
	Estimates	P >| Z |	Estimates	P >| Z |
Log R&D (hat)	0.965	0.031	0.373	0.031
Log sectoral spillovers (hat)	0.254	0.070	0.098	0.070
Log regional spillovers (hat)	-0.245	0.017	-0.095	0.017
Human capital	-0.145	0.666	-0.056	0.666
HK- sectoral spillovers interaction	-0.007	0.882	-0.003	0.882
HK- regional spillovers interaction	0.038	0.078	0.015	0.078
Log of Physical Capital	-0.395	0.123	0.041	0.025
Size (1 if the firm has more than 50 employees)	0.106	0.025	-0.156	0.124
Constant	-12.197	0.011		
Number of obs	417			
Pseudo R2	0.052			

Table 6 reports estimates of the KPF for ‘small’ firms, i.e. those with less than or equal to 50 employees. First and foremost, we can observe that when considering solely small firms, the coefficient on the log of predicted R&D effort is still statistically significant (although only marginally) and its magnitude higher than the value reported in Table 4 though slightly smaller than that observed in Table 5.

The probability of innovating for small firms is positively affected by sectoral knowledge spillovers. Moreover, the coefficient on the log of sectoral spillovers is statistically significant and displays a higher magnitude, i.e. 13% higher than observed in the other two KPF estimations. In line with our expectations, this indicates that sectoral spillovers are comparatively more relevant, as a source of innovation, for smaller firms.

As in the case of 'small and medium' and 'medium-small and small' firms, the log of regional knowledge spillovers enters negatively in the KPF. Moreover, its effect on the small firm's probability of innovating is higher than those reported in Tables 4 and 5: a unit increase in the log of regional spillover leads now to a reduction in the probability of innovating by around 13 percentage points.

Table 6: Knowledge Production Function for small firms (estimation technique: probit)

Dependent variable: Innovation (dummy variable referred to the period 2001-2003)				
	Less than or equal to 50 employees			
	Probit coefficients		Marginal Effects	
	Estimates	P >| Z |	Estimates	P >| Z |
Log R&D (hat)	0.891	0.082	0.348	0.082
Log sectoral spillovers (hat)	0.341	0.048	0.133	0.048
Log regional spillovers (hat)	-0.334	0.028	-0.131	0.028
Human capital	-0.147	0.825	-0.058	0.825
HK- sectoral spillovers interaction	-0.032	0.690	-0.012	0.690
HK- regional spillovers interaction	0.072	0.282	0.028	0.281
Log of Physical Capital	0.131	0.016	0.051	0.016
Constant	-11.690	0.033		
Number of obs	309			
Pseudo R2	0.066			

The coefficients on the interaction terms are not statistically significant. As we observed above, small firms were unable to extract benefits from intramural R&D and this was, perhaps, due to their inability to reach a minimum level of internal knowledge. Hence it should not come as a surprise that knowledge spillovers are not significant when interacting with internal knowledge resources.

Another variable affecting the probability to innovate is the logarithm of physical capital. Specifically, we can observe that one unit increase in the logarithm of physical capital exerted over the period 1998-2000 increases the probability to innovate over the period 2001-2003 by five percentage points.

This empirical analysis suggests that the responsiveness of firms to innovative activities varies with firm size. First, we observed that intramural R&D exerts the highest impact for the sample of medium-small and small firms; whereas sectoral spillovers exert the highest impact on the innovative ability of small firms.

Moreover, when considering the whole sample of small and medium enterprises or a sub-sample of medium-small and small firms, we have found regional knowledge spillovers to be an effective driver of innovation only for well human capital endowed firms. On the other hand – according to the results obtained on the sub-sample of firms with less than 50 employees – small firms do not appear to be able to take advantage of knowledge circulating in their geographical neighbourhood as they typically lack of an adequate level of intramural human capital.

These findings imply that alternative forms of proximity matter for firms of different size. Small-sized firms mainly benefit from knowledge spilling over from firms operating in the same sector (via industrial proximity). On the other hand, larger firms can benefit also from regional spillovers, if they succeed in gaining an adequate intramural level of human capital (via geographical proximity).

5. Conclusions

This paper has attempted to provide some new insights into the ongoing debate on the Italian model of specialization (based on traditional sectors – i.e. the so-called *made in Italy* pattern) and the consequent discussion regarding its adequacy in a global and truly competitive world. We moved from the assumption that "[t]oday there is no such thing as a low-tech industry. There are only low-tech companies – that is, companies that fail to use world-class technology and practices to enhance productivity and innovation" (Porter, 1998: 85-86). Following Porter, this implies that it is possible to find innovative firms enjoying competitive advantages in global markets in all sectors. This theoretical perspective broadens the scope for a policy of *strong competition* (based on innovation, in contrast to *weak competition* based on price competition) for post-Fordist high-income and knowledge-based economies (Asheim, 2000: 7).

Consequently, we investigated firm competitiveness by placing due attention on the determinants of the Italian manufacturing firms' decision to undertake innovative activities. In particular, we investigated two factors which potentially shape innovating patterns: the presence of spillover effects arising from firms operating in the same sector (industrial proximity) and the presence of regional spillovers arising from firms located in the same region (geographical proximity).

We used data on innovative activities and other characteristics of small and medium firms drawn from a Capitalia dataset for the period 1998-2003. To account for the endogeneity of R&D expenditure in the knowledge production function, we estimated the R&D intensity for a firm conditional on being engaged in R&D activity. Subsequently, we used these estimates in a knowledge production function (KPF) estimated (using a standard probit model) for three different samples of firms: the sample of 'small and medium' firms (less than or equal to 250 employees); the subsample of 'medium-small and small' firms (less than or equal to 100 employees); and the sub-sample of 'small' firms (less than or equal to 50 employees).

Our main results are the following: the probability of being engaged in intramural R&D activities does not seem to be significantly related to firm size. However, for those firms engaged in R&D activities, the intensity of R&D effort increases with firm size. By estimating the KPFs disaggregated by firm size, we find the probability to innovate to be positively related to sectoral spillovers. More importantly, the magnitude of such impact decreases with firm size. That is, knowledge spilling over from other firms operating in the same industrial space is essential for small firms and compensates for their limited R&D expenditure. As for knowledge diffusion via geographical proximity, we find that the absorption capacity of firms is strictly dependent on their specific endowment of human capital. This latter result confirms that geographical proximity is not a sufficient condition for knowledge transfer between firms to be effective, as it needs to co-exist with cognitive proximity.

References

Asheim B.T., 2000. The Learning Firm in the Learning Region: Workers Participation as Social Capital, DRUID Summer 2000 Conference, Rebild, Denmark, June 15-17.

Bank of Italy, 2005. Summary of the Reports on economic developments in the Italian regions in 2004. Rome

Barba Navaretti G., Bugamelli M., Faini R., Schivardi F. and Tucci A., 2007. Le imprese e la specializzazione produttiva dell'Italia. Dal macrodeclino alla microcrescita?. Presented at the conference "I vantaggi dell'Italia" Fondazione Rodolfo Debenedetti, Rome, 22 May 2007

Barrios S., Goerg H. and Strobl E., 2003. Explaining firms' export behaviour: R&D spillovers and the destination market. Oxford Bulletin of Economics and Statistics 65(4), 475-496

Becattini G., 1987. Mercato e forze locali: il distretto industriale. Bologna: Il Mulino.

Boschma R.A. 2005. Proximity and innovation: a critical assessment. Regional Studies 39(1), 61-74

Boschma R. A. and Lambooy J.G., 1999. Evolutionary economics and economic geography. Journal of Evolutionary Economics 9, pp. 411-429.

Cantwell J. and Santangelo G. D., 2002. The new geography of corporate research in information and communication technology (ICT), Journal of Evolutionary Economics 12, pp. 163-197.

Capitalia, 2002. Indagine sulle imprese manifatturiere. Ottavo rapporto sull'industria italiana e sulla politica industriale. Rome

Capitalia, 2005. Indagine sulle imprese manifatturiere. Nono rapporto sull'industria italiana e sulla politica industriale. Rome

Cohen W.M., 1995. Empirical studies on innovative activity in Stoneman, P. (ed.). Handbook of the Economics of Innovation and Technological Change, Oxford, Blackwell.

Crépon B., Duguet E. and Mairesse J., 1998. Research, innovation and productivity: an econometric analysis at a firm level. Economics of Innovation and New Technology 7(2), 115-158

Faini R. and Sapir A., 2005. Un modello obsoleto? Crescita e specializzone dell'economia Italiana, in T. Boeri, R. Faini, A. Ichino, G. Pisauro and C. Scarpa (eds.), Oltre il Declino. Il Mulino, Bologna

Forsman M. and Solitander N., 2003. Knowledge transfer in clusters and networks. Journal of International Business Studies – Literature Review, 3

Freeman C. and Soete L., 1997. The Economics of Industrial innovation, 3rd Edition, The MIT Press, Cambridge.

Giuliani E. and Bell M., 2005. The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster. Research Policy 34 (2005) 47–68

Griffith R., Huergo E., Mairesse J. and Peters B., 2006. Innovation and productivity across four European countries. NBER Working Paper 12722

Griliches Z., 1991. The search for R&D spillovers. NBER Working Paper No. 3768

ICE, 2007. Rapporto ICE 2006 – 2007. L'Italia nell'economia internazionale. Rome

Jaffe A., 1986. Technological opportunity and spillovers of R&D: evidence from firms patents, profits, and market value. American Economic Review 76 (5), 984-1001

Howells J.R.L., 2002. Tacit Knowledge, Innovation and Economic Geography. Urban Studies, 39(5–6), 871–884

Kuznets S., 1962. Inventive activity: problems of definition and measurement. In: R.R. Nelson (Ed.) The rate and direction of Inventive activity. National Bureau of Economic Research Conference Report, Princeton University Press, 19-43

Morone P., Sisto R. e Taylor R., 2006. Knowledge Diffusion and Networking in the Organic Production Sector: A Case Study. EuroChoice*s*, 5(3).

Morone P., Petraglia C. and Testa G., 2007. Research, Knowledge Spillovers and Innovation. Birkbeck Working Papers in Economics and Finance, 0713

Morone P. and Testa G., 2008. Firm growth, size and innovation. Economics of. Innovation and New Technology, 17(4), 311-329

Panne van der G., 2007. Issues in measuring innovation. Scientometrics, 71(3), 495–507

Piergiovanni R., Santarelli E. and Vivarelli M., 1997. From which source do small firms derive their innovative inputs? Some evidence from Italian industry. Review of Industrial Organization 12(2), 243-258

Pinch S., Henry N., Jenkins M. and Tallman, S., 2003. From 'industrial districts' to 'knowledge clusters': a model of knowledge dissemination and competitive advantage in industrial agglomeration. Journal of Economic Geography 3(4), 373-88

Porter M., 1998. Clusters and the new economics of competition. Harvard Business Review, November-December, 77-90

Rogers E. M., 1995. Diffusion of innovations. New York, Free Press.

Singh J. 2003. Social networks as drivers of knowledge diffusion. Harvard University. mimeo

Schumpeter J.A., 1942. Capitalism, Socialism and Democracy. New York, Harper.

Smith K., 2006. Measuring Innovation, in: J. Fagerberg, D.C. Mowery, R.R. Nelson (eds.), The Oxford Handbook of Innovation, Oxford University Press.

Technopolis Group, 2006. Strategic Evaluation on Innovation and the Knowledge Based Economy in relation to the Structural and Cohesion Funds, for the programming period 2007-2013. A report to the European Commission, DG Regional Policy. Country report: Italy

Valente T.H., 1995. Network models of the diffusion of innovations. Cresskill, N.J.. Hampton Press.