Sectoral invariances or distance-from-the-frontier effect among European mid-low tech sectors

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Abstract

This study analyses empirically innovative activity among firms operating in mid-low tech sectors in Germany, Italy and Spain. The aim of the paper is to check –within the same sectors across the three countries– whether technology-related sectoral invariances in innovative patterns prevail or innovative strategies depend instead on the level of technological advancement of each national sector. The former case corresponds to the scenario predicted by the sectoral systems of innovation literature, while the latter is consistent with the distance-from-the-frontier framework. On one hand the results of the econometric analysis confirm the presence of some cross-country sectoral-specific features of innovation modes, such as the strong association of R&D activity with process innovation and the strong similarities in the identification of the most important sources of information. However the results also show that the elasticity of R&D to sales changes substantially between Germany and the other two countries. Furthermore it is found that brand-new innovation affects positively the level of sales only in Germany and Italy, while in Spain adoption is more effective, thus highlighting the existence of several differences among innovation modes across countries.

Keywords: Sectoral systems of innovation, distance-from-the-frontier, R&D and productivity

Introduction

The sectoral dimension in innovation studies has been often portrayed as a fruitful line of analysis, able to partially reduce the heterogeneity of behaviors which happens to be observed at the firm level when innovative strategies are concerned (Abernathy, Utterback, 1978; Klepper, 1997; Geroski, Mata 2001). Anyway there is not a common consensus on the expectations about innovative behavior within similar sectors in different countries. One line of analysis has highlighted the role of knowledge and its relevance for the study of technological change within sectors, considering that firms which are in the same sectors and use a similar kind of knowledge should also adopt similar innovative strategies (Malerba, 2002, Audretsch, 1997). The features of the specific knowledge-base used have indeed been considered as determinants both of the way firms innovate and also of the market structures which emerge in different sectors. Within this literature the concepts of technological regimes and sectoral systems of innovation have been developed in order to investigate deeply the influence that knowledge exerts on the array of choices that firms have in order to change and improve their technology. This literature has gone also a step further by predicting that since the specific knowledge used in a sector shapes the possible choices of the firms which are active in that sector, it will also be likely that similar innovative behaviors and competitive structures will be observed in the same sectors across countries (Malerba, Orsenigo, 1996, 1997). There will hence exist some sectoral invariances across countries determined by the fact that the technology used in a sector induces firms to adopt similar behaviors.

Such a perspective is partially in contrast with another line of analysis which has its roots in development economics and identifies the distance from the world technology frontier as the main factor which influences the strategic behavior of innovating firms (Gerschenkron, 1962). According to this literature innovation will differ according to the level of technological development that a country or a national sector has attained. More specifically when a national sector is a leading sector in the international competition, then the major efforts of firms who belong to it will necessarily be devoted to the actual “shift” of the frontier. Within national sectors that are lagging behind or are still catching up instead these efforts will be directed towards the adoption of already existing technologies. According to this perspective hence one would not expect sectoral invariances across countries but rather the choice of the strategy which is locally more advantageous (Antonelli, 1995).

It seems clear that the two perspectives lead to quite different scenarios for a sectoral analysis of innovation and it also seems worth investigating whether these predictions are confirmed by the data. This paper exploits the richness of innovation-related data coming from the Harmonized Community Innovation Survey 4 in order to test the empirical relevance of the two strands of literature: in order to do so it focuses on firms belonging to similar mid-low tech manufacturing sectors in three European countries (Germany, Italy and Spain). Building on a stream of econometric literature aimed at identifying the determinants of innovation and the impact of innovative activities on firms' economic performances (Griffith, Huergo, Mairesse, Peters, 2006), the analysis here is aimed at checking whether firms belonging to similar sectors in different countries really exhibit similarities in innovative behavior or rather adapt their strategies to the environment in which they are embedded.

The paper is organized as follows: Section 1 reviews the existing literature, stressing the difference between the two theoretical paradigms outlined above, Section 2 explains the choice of the sectors analyzed in the three countries and describes the CIS data used, Section 3 explains the methodology used for the empirical analysis, Section 4 describes the results of the econometric analysis and finally Section 5 is dedicated to the discussions and conclusions.

1. Background literature

The hypothesis of the existence of sectoral invariances across countries in innovative patterns has been developed within the theoretical framework of the so-called technological regimes (Nelson, Winter, 1982) and further refined by the sectoral systems of innovation literature (Malerba, 2002). According to this literature the existence of such invariances depends by the role of some features of knowledge such as opportunity, appropriability and cumulativeness conditions, together with the nature of the knowledge itself (Audretsch, 1997; Breschi, Malerba, Orsenigo, 2000; Sutton, 1996). These features are considered as fundamental constraints of technological change and, by affecting the evolution of technology, they have also important effects on the competitive environment of specific sectors. Following this perspective, Malerba and Orsenigo (1997) have linked the characteristics of knowledge to the prevalence of some stylized types of competition identified with the well-known concept of Schumpeter Mark I and Mark II patterns. Building on the evidence coming mainly from patent data they have put forward the hypothesis that the conditions that affect learning and knowledge accumulation would determine similar behaviors across countries within the same sectors. Their results confirmed such patterns, showing how, within the same sectors in different countries, both the indicators concerning market structures and those concerning knowledge features displayed similar values.

These contributions have influenced greatly the following stream of research concerning innovation and the sectoral belonging of firms and have proven to be useful concepts also in the analysis of many other issues related to technological change (Castaldi, 2009; Castellacci, 2007, 2010; Peneder, 2008). Anyway on the empirical ground, to my knowledge, there has not been much evidence able to confirm the existence of uniform patterns of innovation within the same sectors in different countries. On the contrary Malerba and Orsenigo themselves recognized the existence of some differences across countries within the same sectors[1]. Further work on the issue has underlined the relevance of sector-related features of knowledge (Cefis, Orsenigo, 2001) but has also highlighted that part of the variability in innovative behaviors needed to be explained by country specific features (Castellacci, 2009).

On the other hand the stream of literature that focuses on the distance-from-the-frontier effect and that has its roots in the literature on development and technological capabilities (Gerschenkron, 1962; Atkinson, Stiglitz, 1969) has treated the problem of innovation within national sectors from quite a different perspective: it has been underlined indeed that innovation activities should be rather adapted to the specific level of technological development that characterizes a national sector. In the original formulation put forward by Gerschenkron (1962) it is argued that the closer is a country or a sector from the world technology frontier and the more it should rely on brand new research and innovation in order to be able to "shift" the frontier itself. On the contrary firms belonging to sectors which are lagging behind or catching up with respect to the world technological frontier should invest in

[1] Their results showed for instance that Italy and Germany had some structural differences in the way innovation was implemented: while in the first case the entrepreneurial regime (Schumpeter Mark I) based on small innovative firms was more widespread, in the latter the routinized regime (Schumpeter mark II), in which big corporations have a major role in innovation, was often observed (Malerba, Orsenigo, 1997).

the adoption of technologies produced elsewhere. More recently the contribution of Acemoglu Aghion and Zilibotti (2003) has adopted and renewed this perspective by including in the framework also the level of selection of firms and managers as a further element which influences the choice of different innovative strategies: selection will indeed be lower in sectors which are farer from the frontier, where adoption is more frequent, while when a sector is close to the frontier only high-skilled managers able to actually innovate will be capable to bring their firms to economic success. It becomes hence more likely to observe truly innovative and R&D-based firms in technologically advanced national sectors rather than in backward sectors.

Also in this case such predictions are not confirmed by outstanding empirical evidence, Acemoglu *et al.* (2003), using sector-aggregated data from a bunch of OECD countries, show the existence of a positive and statistically significant relation between the proximity to the frontier and the level of R&D intensity. In a similar fashion Madsen *et al*. find (Madsen, Rabiul Islam, Ang, 2010) that in OECD advanced countries R&D affects positively the growth of aggregate total factor productivity through innovation activities, while in developing countries R&D is more effective when used to build absorptive capacity oriented towards imitative strategies. Also at the firm level there have been some attempts to verify the relevance of the distance from the frontier approach. Using microdata from the Community Innovation Survey Holz and Friesenbichler (2010) find that R&D-based innovative strategies have a relevant role only for firms active in countries close to the technological frontier; anyway their results are referred only to high-growth firms. On a slightly different ground Coad and Rao, implementing quantile regressions, show that the stock of R&D has a positive impact on the economic performances of firms (as proxied by their Tobin's q measure), but such impact increases and becomes significant only for firms closer to the frontier, i.e. those firms in the upper quantiles of the Tobin's q distribution. Similar results are obtained by Blundell, Griffith and Van Reenen (1999) who find that innovative activities have a higher impact on market value for firms with a higher market share. It seems hence that R&D-based innovative behavior is a viable solution only for firms which actually are on the technological frontier, while the same is not true for less competitive firms: it would be then highly unlikely to observe the same innovative behavior for firms with different technological capabilities.

Summing up, according to the technological regimes literature firms within the ssame sectors would be bounded by the features of the knowledge used in the choice of their innovative strategies and hence would adopt similar behaviors, also across countries, while according to the distance-from-the-frontier literature firms would have incentives to adopt the strategy that best suits their actual capabilities, hence leading to differentiated behaviors across countries. In the following sections I will try to check empirically the relevance of these two predictions.

2. Data

2.1. The choice of the sample

In order to test the empirical validity of the two streams of literature presented above I chose to focus on a limited number of similar mid-tech sectors in three European countries: Germany, Italy and Spain. Specifically I chose three 2-digit sectors: Rubber and Plastic Products, Other non Metallic Mineral Products and Fabricated Metal Products (except machinery and equipment). These sectors are usually grouped together on the basis of different criteria and can hence provide a homogeneous sample: they are grouped together both by the OECD R&D-based classification (Hatzichronoglou, 1997) as mid–low tech sectors and by the Pavitt classification, as Scale Intensive sectors (Pavitt, 1984). This means on one hand that the degree of formalization of the knowledge used is similar, since the OECD classification is based on the aggregate share of R&D expenditures on value added; on the other hand Pavitt's classification indicates that also a number of other characteristics, such as the way through which the innovative process is implemented, the sources of knowledge and the organization of the productive process, are similar.

The choice concerning the three countries under analysis (Germany, Italy and Spain) was based partly on the availability of data from the CIS 4 and partly on the sake of homogeneity: I chose three comparable countries in terms of size and population of firms and also three sectors for which the total number of observations was sufficient to obtain reliable econometric estimates[2].

Before looking at the firm-level data provided by the CIS 4, I will first present in Figure 1, 2 and 3 some aggregate features of the sectors under analysis during the period 1998-2004, hence in the period which approximately corresponds to the time-span covered by the CIS survey (which refers to 2002-2004). The data come from the OECD STAN database for what concerns labour productivity and employment, while the data on firms' demography proceed from Eurostat's Annual Detailed Enterprise Statistics on Manufacturing.

In Figure 1 are shown the time-series of the (log of) labour productivity of the three sectors in the three countries: the figure highlights the lower levels of productivity of Spanish sectors as compared to the Italian and the German ones, which denote a process of catch up which is not yet concluded (Mas, Milana, Serrano, 2008). This first figure shows that notwithstanding the fact that the three countries are to be considered as advanced capitalistic economies, still there is a quite different level of technological efficiency among them. The variability among the three countries hence provides a first confirmation of the potential relevance of the distance-from-the-frontier approach.

In Figure 2 the growth rates of employment are shown: in this case a general positive growth of employment in the Spanish sectors is observed, while Italian and especially German sectors have gone through a steep decline of the number of person engaged. Figure 3, concerning the yearly rate of growth of the number of firms (Eurostat), completes such framework showing that in the 1998-2000 period a steep increase of the number of firms in the Spanish sectors occurred, thus explaining the great increase of employment. Germany and Italy instead display negative rates of growth on aggregate.

This simple aggregate statistics allow some general considerations about the three sectors in the different countries: although Germany, Italy and Spain are somehow integrated in the same communitarian market and of course cannot be considered as closed economies, nonetheless the statistics show quite different evolutions of their national markets. While German and Italian sectors display the typical behavior of mature sectors with declining

[2] The limited number of observations for each sectors explains also the choice to use three similar (but different) sectors, instead of analyzing only one 2-digit sector per country.

employment and high levels of labour productivity, in Spain these sectors still suffer from a deficit in terms of productivity and hence of the efficiency of the firms involved, but they are somehow in a period of expansion, with a growing number of employees and active firms.

It seems quite clear then that even among advanced European capitalistic countries the general conditions in which firms are active change substantially between one country and another: the distance from the frontier framework, then, might have some relevance. It becomes interesting to investigate whether the way innovative activity is organized within these sectors depends more on the technological features of the knowledge used or, conversely, on the general competitive environment in which firms are embedded.

INSERT FIGURE 1, 2 AND 3 ABOUT HERE

2.2. The CIS data

The firm-level data used in this paper come from the Community Innovation Survey 4 (2002-2004). The CIS is a harmonized survey carried out by national statistical agencies in all 25 EU member states[3] under the coordination of Eurostat. CIS4 was conducted in 2004 and provides information for the period 2002–2004. The data I use have been delivered by Eurostat in micro-aggregated form for reasons of statistical confidentiality (see Appendix A for details).

I built three distinct databases for each of the countries: in each of the national database I included all the firms who responded to the survey and belonged to the three mid-low tech sectors previously selected: after some necessary cleaning procedure, explained in Appendix B, our samples consisted of respectively 526, 1852 and 2126 firms. In Table 3 are reported some descriptive statistics regarding the sectoral composition of our dataset and the means of each of the variables used. As can be easily seen the sectoral composition is very similar in the three datasets, with a larger number of firms belonging to the Fabricated Metal Products

[3] However Eurostat delivers micro-anonymized data from the CIS4 only for the following countries: Belgium, Bulgaria, Czech Republic, Germany, Estonia, Greece, Hungary, Italy, Latvia, Lithuania, Norway, Portugal, Romania, Slovakia, Slovenia and Spain.

sector in all of the samples. The only differences consist in a slightly lower percentage of Fabricated Metal prod. firms in Spain, as compared with Germany and Italy.

INSERT TABLE 1 ABOUT HERE

In Table 3 I also report the mean value of the variables used in our estimations (see Appendix C for a complete definition of the variables used). I hence introduce the four kinds of innovative strategies that I decided to analyze: new to the firm product innovation (adoption/imitation), new to the market product innovation (genuine/ brand new innovation), process innovation and organizational innovation. Before analysing the single variables it must be noted that the average size of the firms in the three databases is comparatively larger in Germany than in Spain and Italy. Italy in particular has the higher percentage of small firms (less than 50 employees), in line with the well-known fragmentation of the Italian productive system, paradoxically even in sectors which are labelled as "Scale Intensive". Given this preliminary remark it's possible to read the descriptive statistics. It must be noted that there is always a lower percentage of firms doing innovation among the Italian sample: even if part of it could be due to a general lower level of engagement (especially when compared with Spain, which has a similar share of small, medium and large enterprises), one must also take into account that small firms do in general less innovation than large corporations.

As for the variables there are some differences and similarities that are worth noting. Among Italian and Spanish firms the main vehicle of innovation is process and organizational innovation, while in Germany product innovation (of both kind: new to the firm and new to the market) is more central in firms' strategies. More than 60% of the surveyed German firms belong to a group, while in Italy and Spain the percentage is much lower. The export-oriented vocation already observed at the aggregate sector level for Germany is mirrored by the high share (again more than 60%) of firms which consider the international markets as the most important. Anyway also in Spain and Italy about half of the firms declare to be internationally oriented. While in Germany clients are the second most important source of information for firms after the firm itself, in Spain and Italy suppliers appear to be more important than clients for the purpose of innovation activities, thus confirming the greater importance of process innovation in the two countries. One last point is dedicated to the importance of professional conferences, trade fairs and meetings (fair variable), which, in these sectors, result to be more important than universities and other higher education institutes.

3. Empirical Methodology

The econometric procedure I implemented in order to identify the main determinants of innovative activity and the effectiveness of each innovative strategy on the performances of firms takes advantage of the contributions made by Griffith *et al.* (Griffith, Huergo, Mairesse, Peters, 2006) with the aim to capture inter-country differences in innovation activity. Conversely from Griffith, anyway, here I apply this procedure to limited sets of sectors and not on manufacturing as a whole. The main intuition behind the estimation procedure is to use a three stage sequential model in which four main equations are supposed to explain the innovative process and its effects on the output of firms: firms decide how much effort they want to invest in innovation, as a result of this effort knowledge is produced and that same knowledge is used as an input in an output production function. A first equation controls for the determinants of the decision to engage or not in innovative activity, if this effort is sufficiently high it will result in the presence of R&D activity. The second equation checks what are the determinants of the intensity of the R&D expenditure. Then in the third equation this innovative effort is used together with other controls in order to measure how it influences the presence of different kinds of innovative outputs. Finally in the fourth equation I measure to what extent these innovative outputs affect firms' output production function. The reason behind this sequential approach lies in the cross-sectional nature of the data: since I am unable to eliminate the unobserved heterogeneity of each firm, it might be expected that such heterogeneity could affect both the decisions concerning the levels of inputs and outputs in my equations implying a bias in the estimates; hence instrumenting the regressors could be a possible way to reduce these endogeneity problems.

3.1. Innovation Inputs

As regards the decision about innovation inputs, I assume that an unobserved latent variable r_i^* describes the innovative effort of each firm, which depends on a set of variables x with coefficients β:

$$r_i^* = x_i^{'}\beta + \varepsilon_i \tag{1}$$

The observed innovative effort is instead proxied by r_i^*, the expenditure in internal and external R&D normalized by the turnover for each firm. In order to have such variable (a share bounded between 0 and 1) normally distributed I take the logarithm of the ratio of R&D expenditures to sales. In my sample firms are asked about their R&D expenditures only if they declare to have introduced product innovation, hence for most of the firms in the sample R&D expenditures are zero, even if they actually had them, but did not introduce any product innovation in the three years covered by the survey. This fact could lead to a typical case of sample selection: it’s necessary to exclude the possibility to have selection bias. In order to do so I estimate a Tobit Type II model (Anemiya, 1984) in which I include a new equation concerning the decision to engage or not in R&D activity, allowing for different coefficient with respect to equation (1). I hence introduce a selection equation:

$$RD_i^* = \begin{cases} 1 \quad if \quad rd_i^* = z_i^{'}\gamma + e_i > c \\ 0 \quad if \quad rd_i^* = z_i^{'}\gamma + e_i \le c \end{cases} \tag{2}$$

RD is a binary variable which equals 1 if a firm declares to have had a continuous engagement in R&D activities and rd_i^* is a latent variable which measures the effort of each firms in innovative activity. If such an effort exceeds a certain threshold level c then the firm will engage in R&D activity. Now it is possible to measure the actual share of R&D expenditure normalised by turnover, conditional on the decision to engage or not in R&D, hence avoiding the selection bias. I have for each firm the following equation:

$$r_i = \begin{cases} r_i^* & if \quad RD = 1 \\ 0 & if \quad RD = 0 \end{cases} \qquad \leftrightarrow \quad r_i = \begin{cases} r_i^* = x_i^{'}\beta + \varepsilon_i & if \quad RD = 1 \\ 0 & if \quad RD = 0 \end{cases} \tag{3}$$

As usual I assume that the error terms of the equation (1) and (2) ε_i and e_i have zero mean and follow a normal bivariate distribution

$$\begin{pmatrix} \varepsilon_i \\ e_i \end{pmatrix} \quad iid \quad \sim \quad \mathrm{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & 1 \end{pmatrix} \right)$$

As explanatory variables in the equations (1) and (2) I use controls for firm-level heterogeneity such as firm size, sector of activity, belonging to a group, the use of intellectual property rights, and –only for firms who declared R&D expenditures– access to local, national or European funding. As in Griffith et al. (2006) with this model I exploit the possibility to use the whole sample of firms, not only those engaged in R&D activities: the presence of R&D expenditures, in fact, is not considered to be the only possible outcome of an innovative effort, especially in mid-low tech sectors where knowledge is not strongly codified (Santamaria, Nieto, Barge-Gil, 2009). Hence at the end of estimation procedure I am able to generate predicted values for all of the firms, thus creating a new variable which measures, according to the two equations estimated, a general propensity towards innovative activity.

3.2. Innovation Outputs

In the next step I want to model a specific equation for the decision to generate innovative outputs, hence knowledge. I consider four kinds of innovative output: product innovation new to the market, product innovation new to the firm (henceforth labelled “adoption”), process innovation and organizational innovation. As Mohnen *et al*. (2009) have shown, the inclusion of organizational innovation is important especially for its relevance in the output production function. The stress on the difference between the “height” of innovations, carried on through the differentiation between the two types of product innovation, is instead in line with Duguet's contribution (2006)[4]

I then have an equation in which I try to identify the determinants of the different kind of innovation output using, among other control variables, the predicted values of the latent innovative effort r_i^* that I obtained from equation (2). In this way not only I have a measure of innovative inputs in terms of unobserved effort for the whole sample of firms, but also I am instrumenting the innovative inputs variable which is likely to be endogenous to the results of innovation output. One might expect, indeed, that omitted characteristics of the firms which are not observable (and that cannot be eliminated, since these are only cross-sectional samples) affect both the innovative effort of the firms and their capacity of translating this effort in actual innovations. If this were so one would have biased estimates because of the correlation between r_i^* and the error term v_i. The innovation equations are:

$$k_i = \hat{r}_i^* \alpha + x_i' \delta + v_i \qquad (4)$$

In equation (4) k is a dichotomous variable which is equal to 1 if a firm introduced an innovation. I have 4 different equations in which the dependent variable is respectively product innovation (of the two kinds), process innovation and organizational innovation. $\hat{r}_i^*$ is the predicted level of R&D intensity from equation (1) and x_i is a set of explanatory variables. I estimate these innovation equations as four separate probit equations by maximum likelihood.

3.3. Production function

In the last step I estimate a production function in which the dependent variable is the log of turnover and the regressors are the predicted values of process, product (of the two type) and organizational innovation, the log of investments in physical capital and a proxy for labour given by the three dimensional dummies for the number of employees. The utilization of the

[4] Differently from Duguet : here I use this different classification between radical innovation and adoption only for product innovation and not for innovative processes, as in Duguet (2006).

predicted values for the different kinds of innovation output allows to contrast the possible endogeneity of such variables, for the same reasons of equation (4). The production function is estimated with OLS and is the following:

$$y_i = a + \sum_j \hat{k}_{ij}^{'}\theta_{1j} + c_i^{'}\theta_2 + l_i^{'}\theta_3 + x_i^{'}\beta + u_i \qquad \text{with} \qquad j = 1,....,4 \tag{5}$$

Where y_i is the log of turnover, $\hat{k}_{ij}$ are the predicted probabilities of the realization of each of the four innovation outputs alone, c_i is (the log of) physical capital, l_i are the size dummies for employment, x_i is a set of control variables that account for country and sector effects and a represents the log of the average level of efficiency. The estimated coefficients are elasticities and semi-elasticities of the independent variables with respect to firm's turnover[5].

4. Results

R&D equations

In Table 2 are presented the results for equations (1) and (2) concerning the decision to engage continuously on R&D and on the actual amount of resources invested in it. The results from the tobit specification show a very similar picture in the three samples for what concerns the decision to engage or not continuously in R&D. Equation (2) in fact displays very similar coefficients: competing in international markets and issuing patents is, not surprisingly, positively associated with R&D activities, in line with previous contributions (Griffith *et al.*, 2006; Brouwer, Kleinknecht, 1999). Belonging to a group instead displays a small and not significant coefficient. Also size is positively related with the continuous engagement in R&D activities (Cohen, Klepper, 1996; Cohen, Levin, Mowery, 1987); since I prefer to have a continuous measure of size I use the log of sales as a proxy for it, instead of using the

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[5]We are thus assuming to face a production function of the following kind: $Y_i = AC_i^{\alpha} \exp\left(\sum_j \beta_j INNO_{ij} + \sum_n \gamma_n SIZE_{in} + \sum_m \delta_m CONTROLS_{im} + u_i\right)$ in which α is the elasticity of physical capital and β, γ and δ are the semi-elasticities for, respectively, the presence of the various kinds of innovation, the size dummies and the other controls for country and sectoral effects.

employment dummies. Such a choice turns out to be interesting in the estimation of equation (1) concerning the intensity of R&D activity (proxied by the R&D to sales ratio), because it allows to estimate the elasticity of size to R&D. In Table 2 in fact in the last three columns I have the intensity equations, from which I can derive the elasticity of sales to R&D expenditures[6] (always controlling for selection bias). A huge literature has dealt with this issue (see Cohen and Levin, 1989) and more recently Crepon *et al.* (Crepon, Duguet, Kabla, 1996) found an elasticity not significantly different from one (constant returns) in the French manufacturing sector (see also Cohen, Klepper, 1996). In our estimates constant returns are confirmed for Germany, where the elasticity amounts to 1, while among Italian and Spanish firms I find a quite lower coefficient of respectively 0.8 and 0.45. These findings seem to confirm that the growth (in terms of sales) of Italian and especially Spanish firms is not always supported by corresponding investments in formalized knowledge, thus supporting the distance-from-the-frontier approach according to which for firms distant from the frontier the importance of formalized innovative activity is smaller (Acemoglu, Aghion, Zilibotti, 2003).

INSERT TABLE 2 ABOUT HERE

Among the other determinants of R&D intensity the binary variable "belonging to a group" displays in this equation a positive and significant semi-elasticity in Italy and Spain but not in Germany: this is quite comprehensible, since from the descriptive statistics it has been observed that 60% of German firms belonged to a group. In Italy and Spain, instead, where the presence of small and medium enterprises is more common, it seems likely that firms which can access finance and knowledge from within the conglomerate (Mohnen *et al.* 2009) have a competitive advantage when it comes to invest in knowledge.

[6] The equation for the elasticity of sales to R&D is:

$$\ln(R\,\&\,D_i) = \ln(sales_i)\beta + x_i^{'}\delta + \varepsilon_i$$

where ε is the elasticity of sales to R&D, while in columns (4), (5) and (6) we have:

$$\ln(R\,\&\,D_i / sales_i) = \ln(sales_i)(\beta - 1) + x_i^{'}\delta + \varepsilon_i$$

As the rho coefficient shows, the selection bias problem is confirmed for all of the three national samples of firms, thus confirming the importance of using appropriate measures to avoid it.

Innovation equations

In Table 3 are presented the results from the probit estimations of equations (4); since I am using the predicted values from the Tobit equations I have a measure of innovation input (effort) also for those firms who actually have zero or missing values for R&D expenditures, thus assuming that these firms may still make innovative efforts even if not through formalized R&D activity.

INSERT TABLE 3 AND 4 ABOUT HERE

First of all one can notice the poor estimates of the coefficients of R&D intensity on the introduction of brand new innovations and on the adoption of new products already existing in the market: this is quite peculiar of these industries, since in most of previous studies instead R&D was found to affect especially product innovation. Interesting results comes then from the process innovation equation: while in most of the previous studies R&D did not have a fundamental role in this kind of innovation (Griffith *et al*., 2006; Mairesse and Robin, 2009), here a quite different pattern is observed. The coefficient of R&D intensity, in fact, is not only significant in Germany and Spain, but also displays higher values than in the case of brand new product innovation and of all the other type of innovation. In Italy the coefficient for R&D, although positive, remains not significant. Parisi *et al.* (Parisi, Schiantarelli, Sembenelli, 2006) are among the few who tried to carefully treat such a relationship: however what they found was only a positive value of the interaction term of investment in fixed capital and R&D, suggesting some kind of absorptive capacity effect of R&D expenditures. Here instead it is the coefficient of R&D which directly influences process innovation. Even if the cross-section nature of our database prevents us to state clear relations of causality (which could instead be possible with repeated observations), it seems legitimate to interpret this coefficient as a typical sectoral feature of innovation, which is usually not observed when the sectoral element is not taken into account.

Patenting activity is positively related with all kinds of innovative activity among Spanish firms, but not among German and Italian firms. In these two countries instead patents are associated mainly with brand new product innovation, quite in line with the expectations. In particular both countries show even negative coefficients for patents in the process innovation equation, highlighting how the two strategies (process innovation and patent-related innovative activity) are to be considered as alternatives.

The employment dummies are always positive and significant for Italian firms, denoting the substantial absence of innovative activities among small companies, and mildly positive in Spain. In Germany instead the dummies are significant only for organizational innovation, thus highlighting how the more competitive environment pushes also small firms to introduce innovations of all kinds. This findings seem to confirm again the different competitive forces that are at stake in the three countries: in Germany all firms, whether large or small, need to have the capability to innovate in order to survive, contrary to what happens in Italy and Spain.

Among the sources of information interesting regularities emerge: internal capabilities are important for all kinds of innovations, in Spain and Italy they are especially important for process innovation. Clients are extremely important for all types of product innovation, thus highlighting the role of user-producers linkages (Von Hippel, 1988) in these specific sectors. For the adoption of a product already in the market clients are as important as competitors, hence suggesting that firms may decide to adopt competitors' products only after that their own clients have expressed satisfaction for such new technologies. Another important source of information for the adoption of new products are trade fairs and business conferences. University laboratories instead almost never have positive or significant coefficients confirming the different patterns of innovation in mid-low tech sectors as compared with the other manufacturing sectors (Von Tunzelmann, Acha, 2005). As expected suppliers are of extreme importance for the implementation of process innovations only.

Finally considering organizational innovation, which has been included as a further control in the production function equation of the next step, although the coefficients of the variables are often significant, specifically the size variables, the overall explicative power of the regression are very low when looking at the Pseudo R-squared in Table 5. The determinants of this kind of non-technological innovation are probably of a different kind with respect to the other three kind of innovation. Further research should be indeed addressed towards this direction.

Production function

Finally in Table 7 are presented the results for the OLS estimation of the output function. I regress the log of turnover on the log of machinery acquisition (investment in physical capital), the predicted values of the probit estimations for each kind of innovative output, finally on the employment dummies used as proxies for labour and I control for the presence of sectoral effect with the introduction of the relative dummies.

INSERT TABLE 5 ABOUT HERE

Since I don't have the stock of capital, but only the investments in the years between 2002 and 2004, I am not using a proper measure of capital: for what concerns Italian firms, anyway, the results are quite in line with the related literature (Mohnen et al.,2009, Griffith et al., 2006). In Germany a lower elasticity of capital is observed, while in Spain the coefficient of capital is surprisingly negative and significant: this could be due to the fact that I am using a flow measure of capital (investments) instead than a stock and hence I am facing a large number of zero values in the firms' distribution of the expenditures in machinery[7].

[7] Also Griffith *et al.* (2006) found a lower elasticity of investments to labour productivity for Spain, with respect to Germany and France, although in their case the coefficient remained positive. In order to check if the zero values of investments affected our estimates, we ran the same production function estimations only for firms which had positive expenses in machinery. The results (available on request) show that the coefficient of "capital" increases proportionally in each of the three countries, leading to positive values also for Spain (about

For what concerns the semi-elasticities of the different kind of innovation output with respect to turnover one can observe some very interesting results. I first excluded organizational innovation, in order to test if excluding it could lead to a omitted variable problem. The estimates display two quite distinct results: while in Germany and Italy only brand new product innovation has a positive and significant coefficient, among Spanish firms product adoption is the only positive (and quite large) coefficient, while the introduction of a product which is new also for the market has a negative and significant coefficient. Process innovation instead in all of the countries is significantly negative. Such a result on process innovation, anyway, can be explained by the fact that I am using sales as a dependent variable and hence I am incorporating in my estimates the demand shift effect and the temporary monopoly rent of innovators, which is clearly associated with product innovation and not with process innovation.

Finally I check how introducing organizational innovation might affect my previous estimates: again the results are interesting. As for Germany and Spain organizational innovation displays a small coefficient, when compared with the other proxies of technological innovation, also the coefficient of product and process innovation remain unaffected, hence showing the inexistence of a consistent omitted variable problem. In Italy instead organizational innovation displays the higher coefficient among the four kind of strategies and its introduction also affect the coefficient of brand new product innovation, which then becomes not significantly different from zero. Capital elasticity instead is never affected by the introduction of organizational innovation, not even in Italy, where the coefficient remain around 0.18.

When comparing these results with previous contributions (Mairesse and Robin, 2009; Griffith et al.,2006; Mohnen et al, 2009), it is evident that the coefficients of the four kinds of innovation are quite large. A possible explanation lies in the lack of a continuous measure for labour, which here is only proxied by the employment dummies. One might in fact expect some kind of omitted variable bias: assuming a positive correlation between size and the presence of innovation outputs (which our empirical results have proven to be present, even if

0.10). The coefficients of the innovative variables are instead left unchanged, confirming the different role of each of the innovative dummies for the different countries, as observed in the original sample.

not always in a significant way) there might be a positive bias on such coefficients. This would explain these very high levels of the impact of innovation on sales.

5. Conclusions

In this paper I have been interested in checking whether innovative activity within sectors depends more on the nature of technology used –and hence displays sectoral invariances across countries– or it is influenced by the specific context in which firms are embedded –and hence display significant cross-country differences.

Our results give two different signals which seem to indicate that the two streams of literature might be fruitfully complemented with each other. On one hand I find a number of sectoral invariances across the three countries analyzed in the innovative behavior of firms, in line with the literature on the sectoral systems of innovation and with the hypothesis of common technological opportunities (Nelson, Winter, 1982; Malerba, Orsenigo, 1997; Malerba, 2002). On the other hand the results also highlight substantial differences between the three countries, especially for what concerns the effectiveness of different innovative strategies, which appear to be more in line with the distance from the frontier literature.

My results in fact show that there are strong similarities in the determinants of firms' innovative output: specifically I find that R&D efforts are especially directed towards the implementation of process innovations, differently from the results obtained when similar analyses are applied on the total set of manufacturing firms (Griffith, Huergo, Mairesse, Peters, 2006), in which a tighter link was found between R&D expenditures and product innovation. Also the sources of knowledge which are considered of high importance by the firms display high degree of homogeneity across the three countries, particularly it seems worth recalling the absence of University sources among the most important channels of spillovers. Clients, suppliers and trade fairs, instead display on average a much higher relevance, thus underlining the importance of more informal types of knowledge in the developing of new products and processes in these specific sectors. The prediction of the existence of sectoral invariances finds hence confirmation in the empirical evidence.

However some important differences between the three sample emerge as well, which highlight the importance to take into account also the distance-from-the-frontier-approach. Specifically I find that the elasticity of R&D to size varies a lot between technologically advanced countries like Germany and countries which show a lower level of aggregate labour productivity such as Italy and Spain. Italian and Spanish firms in the three sectors display a lower elasticity of R&D to sales and thus confirm the existence of differentiated patterns of organization of innovative activities in the same sectors across countries.

Furthermore the results show that when it comes to the effectiveness of innovative output on the economic performances of firms the picture is more mixed than what the technological regimes literature would predict: in line with the distance to the frontier literature I find that brand new innovation is effective only for firms active in sectors close to the technological frontier. In national sectors which are still distant from the technological frontier, such as in the case of Spanish sectors, strategies focused on the adoption of technologies already invented by other firms seem to guarantee higher level of economic success. These evidence is much more consistent with the view that according to their distance from the world technological frontier firms will be more or less induced to innovate or to imitate (Acemoglu Aghion, Zilibotti, 2003).

Summing up the results show that both approaches need to be considered when sectoral analysis on innovative activities are performed: the technological regimes literature is extremely relevant for the identification of the main determinants of the innovative activity *per se*, and this seems quite in line with the analyses of Malerba and Orsenigo (1996, 1997), which were based on patent data, hence on measure of the innovative activity and not of its exploitation. When instead the actual introduction in the market of innovations is concerned and the decisions concerning the investment of profits in R&D activities are involved the literature on the distance from the frontier becomes relevant showing that firms within similar sectors differentiate their strategies according to the competitive environment in which they are embedded. The importance of these two sides of the coin should be kept in mind whenever sector-specific industrial policies are implemented: the knowledge-related features of technology need necessarily to be taken into account, but then another necessity is to fine-tune each decision on the specific context in which firms are active.

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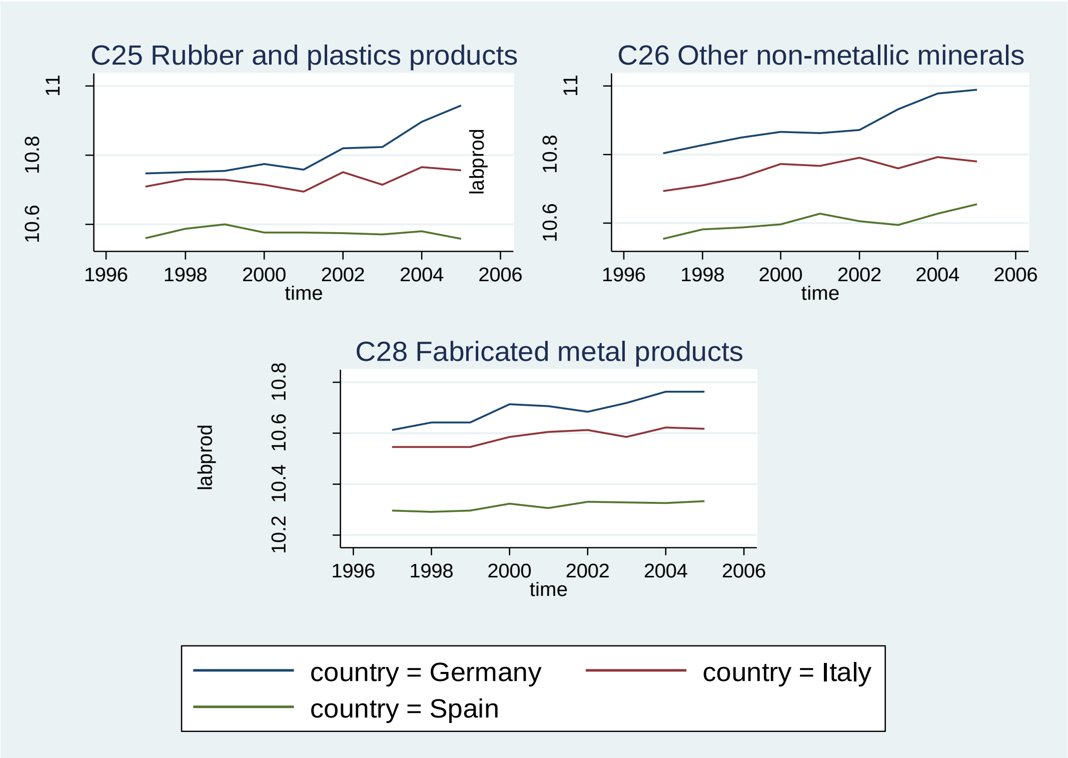
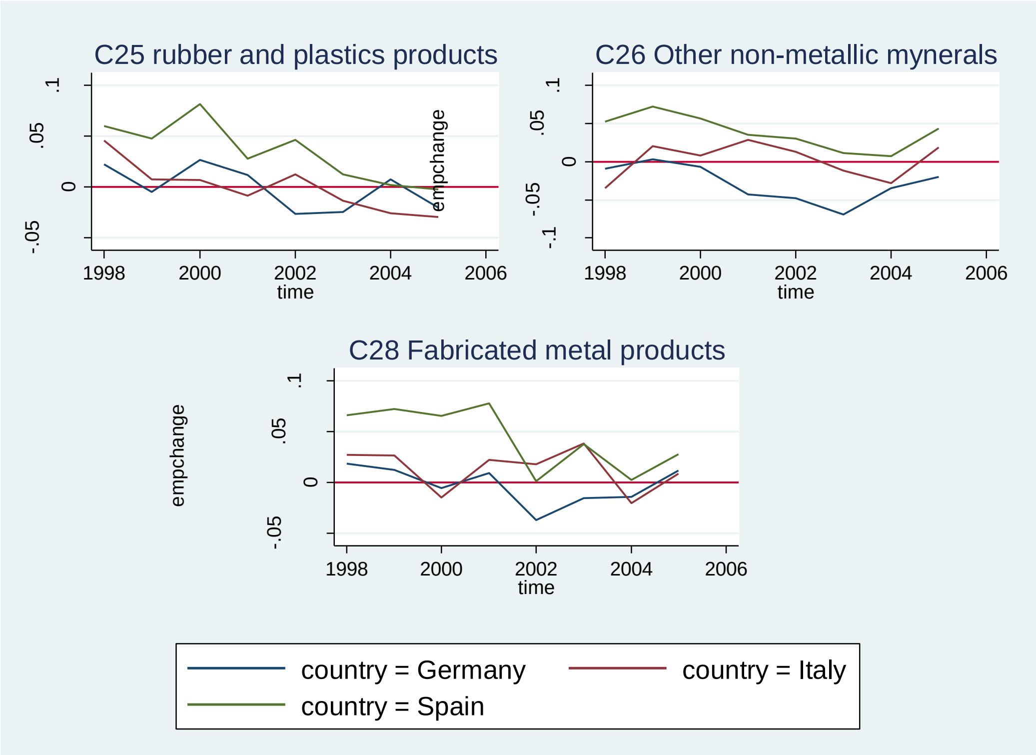
Figure 1. Dynamics of (log) labour productivity



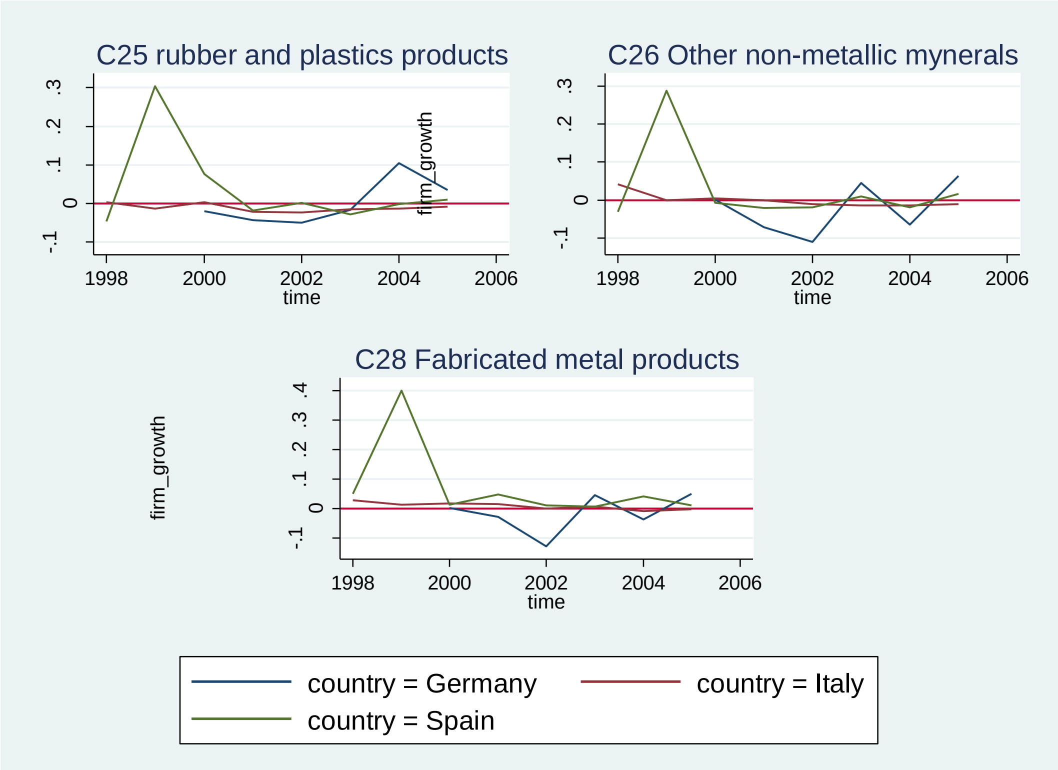
Source: own elaborations on OECD STAN (2011)

Figure 2. Yearly rate of growth of employment



Source: own elaborations on OECD STAN (2011)

Figure 3. Yearly rate of growth of the number of active firms



Source: own elaborations on Eurostat (2011)

Table 1. Means of Variables in the Three Samples

Variables	Germany	Italy	Spain
Sectoral composition			
C25 Rubber and Plastics	0,278	0,173	0,228
C26 Other non Metallic Minerals	0,171	0,275	0,333
C28 Fabricated Metal Products	0,551	0,552	0,439
Innovation			
R&D intensity	0,013	0,004	0,008
Investment Intensity	0,015	0,016	0,009
Product innovation new to the market	0,319	0,117	0,154
Product innovation new to the firm	0,481	0,134	0,238
Process innovation	0,356	0,271	0,325
Organizational innovation	0,536	0,356	0,353
Structural			
Turnover in 2004 (in logs)	16,100	15,233	15,417
Belonging to a group	0,606	0,187	0,231
International markets	0,625	0,490	0,563
Cooperation in innovation activity	0,198	0,050	0,142
Formal protection	0,312	0,110	0,124
Funding			
Local funding	0,118	0,111	0,163
National funding	0,093	0,075	0,103
European funding	0,084	0,022	0,033
Sources of information			
Internal sources within the enterprise or group	0,418	0,133	0,251
Suppliers as a source of information	0,169	0,098	0,124
Clients as a source of information	0,319	0,062	0,115
Competitors as a source of information	0,122	0,024	0,055
University as a source of information	0,044	0,006	0,033
Trade fair and conferences as a source of information	0,110	0,041	0,055
Size			
less than 50	0,399	0,674	0,579
50 -249	0,365	0,262	0,348
more than 250	0,236	0,063	0,073
Observations	526	1852	2126

Source: Eurostat's CIS 4 data (2002-2004)

Table 2. Tobit estimates of R&D equations: R&D selection and R&D intensity

Dependent variable	Engagement in R&D (marginal effects)			(log of) R&D to sales ratio		
Sample	*Germany*	*Italy*	*Spain*	*Germany*	*Italy*	*Spain*
	(1)	(2)	(3)	(4)	(5)	(6)
Turnover in 2004 (in logs)	0.067***	0.051***	0.054***	-0.086	-0.190**	- 0.546***
	(0.015)	(0.006)	(0.007)	(0.072)	(0.084)	(0.055)
Belonging to a group	0.011	0.014	0.034	0.058	0.440**	0.447***
	(0.046)	(0.020)	(0.022)	(0.209)	(0.171)	(0.117)
International markets	0.155***	0.066***	0.136***	-0.276	0.249	0.525***
	(0.045)	(0.016)	(0.018)	(0.313)	(0.204)	(0.176)
Patenting activity	0.338***	0.224***	0.246***	0.382	0.556**	0.334**
	(0.052)	(0.036)	(0.033)	(0.292)	(0.232)	(0.150)
Local funding	-	-	-	0.568**	0.090	0.380***
	-	-	-	(0.239)	(0.123)	(0.104)
National funding	-	-	-	0.346	0.218	0.750***
	-	-	-	(0.247)	(0.138)	(0.125)
European funding	-	-	-	0.192	0.049	0.162*
				(0.161)	(0.173)	(0.083)
Sectoral Dummies	yes	yes	yes	yes	yes	yes
Constant	-	-	-	-3.531***	-3.256*	2.894***
	-	-	-	(1.309)	-1.807	(1.097)
rho	-	-	-	0.471**	0.695***	0.373**
	-	-	-	(0.186)	(0.164)	(0.165)
Wald test of indep. eqns.(rho = 0)	-	-	-	4.58	7.26	4.17
p-value	-	-	-	0.032	0.007	0.041
Log-pseudolikelihood	-	-	-	-452.7683	-960.418	- 1445.595
Observations	526	1852	2126	526	1852	2126

Robust standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Marginal effects of innovation equations

Dependent variable	Product adoption			Brand new product innovation		
sample	*Germany*	*Italy*	*Spain*	*Germany*	*Italy*	*Spain*
	(1)	(2)	(3)	(4)	(5)	(6)
predicted R&D intensity	0.073	0.046*	0.006	0.116	0.010	0.042***
	(0.094)	(0.025)	(0.018)	(0.077)	(0.026)	(0.014)
Investment Intensity	0.045***	0.018***	0.020***	0.012*	0.013***	0.001
	(0.007)	(0.002)	(0.003)	(0.007)	(0.002)	(0.002)
International markets	0.138**	0.013	0.068***	0.142***	0.008	0.027
	(0.060)	(0.013)	(0.021)	(0.050)	(0.013)	(0.017)
Patenting activity	0.122*	0.038	0.199***	0.176***	0.188***	0.233***
	(0.073)	(0.027)	(0.037)	(0.064)	(0.049)	(0.034)
Size						
50 -249	-0.084	0.061***	0.019	0.041	0.034**	0.056***
	(0.061)	(0.017)	(0.026)	(0.057)	(0.017)	(0.021)
>250	0.117	0.114***	0.108**	0.141*	0.088***	0.173***
	(0.080)	(0.045)	(0.054)	(0.076)	(0.039)	(0.055)
Sources of information						
Internal	0.087	0.050***	0.187***	0.169***	0.071***	0.157***
	(0.056)	(0.019)	(0.027)	(0.049)	(0.023)	(0.023)
Suppliers	-0.063	0.014	0.035	-0.047	0.012	0.024
	(0.071)	(0.017)	(0.032)	(0.056)	(0.017)	(0.024)
Clients	0.160***	0.072***	0.184***	0.052	0.067***	0.122***
	(0.057)	(0.031)	(0.040)	(0.051)	(0.032)	(0.032)
Competitors	-0.049	0.079**	0.107**	-0.013	-0.003	0.028
	(0.080)	(0.054)	(0.051)	(0.068)	(0.029)	(0.034)
University	-0.104	0.046	0.056	-0.056	0.194*	0.051
	(0.135)	(0.090)	(0.063)	(0.101)	(0.149)	(0.046)
Trade fairs	0.177**	0.038*	0.146***	0.109	-0.004	0.071*
	(0.080)	(0.027)	(0.054)	(0.078)	(0.019)	(0.039)
Sectoral Dummies	yes	yes	yes	yes	yes	yes
Pseudo R_squared	0.219	0.349	0.207	0.213	0.300	0.260
Log-likelihood	-284.406	-474.670	-925.176	-259.189	-380.613	-674.759
Observations	526	1852	2126	526	1852	2126

Robust standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Marginal effects of innovation equations

Dependent variable	Process innovation			Organizational innovation		
sample	*Germany*	*Italy*	*Spain*	*Germany*	*Italy*	*Spain*
	(1)	(2)	(3)	(4)	(5)	(6)
predicted R&D intensity	0.288***	0.066	0.054**	0.055	-0.082	0.036*
	(0.086)	(0.053)	(0.022)	(0.086)	(0.061)	(0.021)
Investment Intensity	0.047***	0.071***	0.038***	0.020***	0.017***	0.022***
	(0.007)	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)
International markets	0.216***	0.032	0.127***	0.062	0.095***	0.056**
	(0.052)	(0.024)	(0.025)	(0.058)	(0.028)	(0.026)
Patenting activity	-0.092	-0.060	0.166***	-0.164**	0.150***	0.151***
	(0.064)	(0.035)	(0.041)	(0.071)	(0.055)	(0.037)
Size						
50 -249	0.093	0.059**	0.039	0.109*	0.064**	0.094***
	(0.057)	(0.030)	(0.031)	(0.056)	(0.031)	(0.031)
>250	0.046	0.125**	0.219***	0.214***	0.118**	0.242***
	(0.076)	(0.064)	(0.060)	(0.072)	(0.057)	(0.056)
Sources of information						
Internal	0.106**	0.112***	0.323***	0.009	0.072*	0.168***
	(0.052)	(0.040)	(0.030)	(0.054)	(0.038)	(0.029)
Suppliers	0.209***	0.106***	0.177***	-0.063	0.118***	0.149***
	(0.068)	(0.044)	(0.044)	(0.068)	(0.043)	(0.039)
Clients	0.021	0.065	0.167***	0.187***	0.034	0.052
	(0.054)	(0.050)	(0.048)	(0.053)	(0.052)	(0.041)
Competitors	0.016	-0.099***	0.045	-0.008	-0.096	0.034
	(0.071)	(0.025)	(0.064)	(0.078)	(0.069)	(0.056)
University	-0.118	-0.041	0.023	0.043	-0.125	0.118
	(0.096)	(0.083)	(0.079)	(0.130)	(0.142)	(0.075)
Trade fairs	0.119	-0.001	0.182***	0.198***	0.095	0.138**
	(0.075)	(0.043)	(0.066)	(0.072)	(0.062)	(0.057)
Sectoral Dummies	yes	yes	yes	yes	yes	yes
Pseudo R_squared	0.237	0.553	0.296	0.091	0.073	0.131
Log-likelihood	-261.095	-482.772	-943.770	-329.889	-1117.584	-1199.3661
Observations	526	1852	2126	526	1852	2126

Robust standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Estimates of the production function equation

Dependent variable	Log of turnover		Log of turnover		Log of turnover	
sample	*Germany*		*Italy*		*Spain*	
	(1)	(2)	(3)	(4)	(5)	(6)
Product innovation (brand new)	2.585***	2.829***	1.517***	-0.075	-2.777***	-2.698***
	(0.420)	(0.620)	(0.261)	(0.336)	(0.332)	(0.359)
Product innovation (adoption)	-0.729	-1.093	-1.794***	-2.548***	4.353***	4.313***
	(0.512)	(0.832)	(0.304)	(0.311)	(0.455)	(0.461)
Process innovation	-1.528***	-1.570***	-2.136***	-3.140***	-0.932***	-0.712
	(0.275)	(0.284)	(0.186)	(0.292)	(0.246)	(0.435)
Organizational innovation		0.335		4.577***		-0.376
		(0.540)		(0.421)		(0.606)
(log of) Investment	0.055***	0.059***	0.168***	0.183***	-0.038***	-0.037***
	(0.014)	(0.016)	(0.012)	(0.014)	(0.007)	(0.007)
Size						
50 -249	1.598***	1.536***	1.892***	1.514***	1.868***	1.888***
	(0.093)	(0.145)	(0.044)	(0.059)	(0.040)	(0.051)
>250	3.174***	3.113***	3.390***	2.783***	3.427***	3.461***
	(0.113)	(0.153)	(0.078)	(0.104)	(0.078)	(0.094)
Sectoral dummies						
Fabr. Metal Prod.	0.141	0.129	-0.226***	-0.398***	-0.261***	-0.253***
	(0.108)	(0.109)	(0.043)	(0.042)	(0.043)	(0.045)
Rubber and Plast.	0.199*	0.160	-0.003	-0. 144**	-0.015	0.002
	(0.113)	(0.130)	(0.057)	(0.057)	(0.049)	(0.057)
Other non met. min.						
Constant	14.330***	14.288***	14.595***	13.631***	14.409***	14.450***
	(0.144)	(0.153)	(0.039)	(0.093)	(0.042)	(0.079)
Observations	526	526	1852	1852	2126	2126
R-squared	0.802	0.802	0.705	0.734	0.665	0.665

Robust standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%