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DO INNOVATIVE INPUTS LEAD TO DIFFERENT INNOVATIVE OUTPUTS IN MATURE AND YOUNG FIRMS?

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Abstract

This paper investigates the determinants of different types of innovative inputs (R&D and technological acquisitions) and their relationship with different innovative outputs (product and process innovation) by distinguish among firms of different age (mature vs young). In doing so we apply a nonlinear structural model estimated on the third and fourth waves of the Italian Community Innovation Survey (CIS).

We find that firm and market characteristics play a distinct role in boosting different types of innovation activities for firms of different age. In particular, while the methods of appropriability, and the international market exposure are relevant for both innovative inputs, the cooperation in innovation activities appears to be important to increase the level of investment in R&D but not in technological acquisition. Moreover, young firms show a higher level of sensitivity than their mature counterparts to the sources of information to innovation when looking at the magnitude of their innovative effort. On the contrary, factors like methods of appropriability and support to innovation appear to be more important in enhancing the level of investment in both R&D and technological acquisitions, for the mature firms only. Finally, the two innovative inputs appear to be equally important in determining both innovative outputs for the two sub-samples of firms.

Jelcodes:O31,-

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Keywords: R&D, technological acquisitions, innovative outputs, young firms.
JEL Classification: O31.

1. Introduction

Historically, technological innovation has been recognised as one of the major source of growth and development (Solow, 1956; Romer, 1986). Recently, thanks also to the increased availability of micro-level data from innovation surveys, we have assisted to a flourishing interest on this subject (see Hall *et al.*, 2010 for a recent review on the subject). Starting from the seminal work of Crepon *et al.* (1998), many researchers have tried to explain economic growth by technological outputs and the latter by technological effort. In general, results have shown a clear-cut positive relationship between R&D and innovation on the one hand, and different measures of economic growth on the other hand.

However, most of these studies have invariably omitted to take into account the high degree of heterogeneity associated with firm innovation. Apart from internal formalised R&D, firms can also rely on different external sources of innovation, like technological acquisition, with particular reference to the part of technological change embodied in the acquired goods (as in the case of acquisition/substitution of machinery and equipment).

In addition, as shown by recent evidence (see Santamaría *et al.*, 2009; Ortega-Argilés *et al.*, 2009 and 2010) specific firm and market characteristics played a vital role in determining different firm's innovative strategies, both in terms of innovative inputs and outputs. Among these peculiarities, firm's size and firm's age can be certainly considered as the most important (Acs and Audretsch, 1987; Audretsch, 1995; Huergo and Jaumandreu, 2004). Traditionally, however, it has been shown more interest in analysing possible differences in the innovative behaviour of small and large firms than of mature and young ones. Nevertheless, young firms in general and innovative young firms in particular, are often seen as key actors in economic growth and job creation (Birch, 1979; Acs and Audretsch, 1990; Brüderl and Preisendorfer, 2000). Foster *et al.* (2001) show that one third to one half of aggregate productivity growth in US manufacturing is directly attributable to creation of new firms, reallocation between firms, and disappearance of unsuccessful ones. Other studies have focalised their attention on the relative position of disadvantage of the European context in creating the necessary condition to the born and growth of the so-called Young Innovative Companies (YICs). In this respect, some evidence suggest that EU start-ups face higher barriers to entry, innovate and growth compared to their US counterparts (see Bartelsmann *et al.* 2004, Philippon and Véron, 2008). Accordingly, in the last few years, several EU member States have been promoting policy intervention aimed at encouraging the establishment, consolidation and development of YICs (Schneider and Veugelers, 2010; Moncada-Paternò-Castello, 2011).

In this line, the aim of this paper is twofold. Firstly, we try to analyse the determinants of the firms' innovative effort (distinguish between R&D and technological acquisitions) and its link with the different outcomes (in terms of product and process innovation) that the same effort produces. Secondly, we try to shed some light on how these particular relationships differ between young and mature incumbent firms.

With this aim, using the third and the fourth waves of the Italian Community Innovation Survey (CIS), we run a recursive model that can be seen as an extension of a Crépon, Duguet and Mairesse's (1998) partial structure model (hereafter CDM model) to analyse these relationships[1]. Apart from the distinction we make among firms of different age, this is one of the first studies to include in a CDM model context technological acquisition (TA) as an additional innovation input besides R&D. Moreover, in contrast with most previous studies using CIS data, we implement an empirical strategy that takes into account the divide between innovative and not innovative firms in order to correct for a well-known problem of sample selection.

Following this introduction, the next section provides a discussion of the theoretical framework on which this work is based. Section 3 outlines the econometric methodology adopted. Section 4 describes the database and the variables used in our analysis. Section 5 discusses our empirical results and, finally, Section 6 highlights our main conclusions.

2. The literature

In his seminal contribution, Griliches (1979) suggests a model of technological change according to which innovative outputs are seen as the product of knowledge generating inputs. More in detail, the author proposes a three equations model in which one of them is a function (the so-called Knowledge Production Function (KPF)) that links a measure of innovative input (namely R&D) with a measure of innovative output (namely Patents)[2].

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[1] The lack of data on firms' productivity prevented us from estimating the last equation of the classic CDM model (see next section for a more detailed description of the model).

[2] The other two equations in the model represent the determinants of R&D investment and the production function (augmented by the innovation term).

Following this insight, Crèpon Duget and Mairesse (1998) developed a more comprehensive model based on three distinct, but interrelated relationships: 1) the innovation input linked with its determinants; 2) the KPF that connects innovation input to innovation output; 3) the productivity equation, in which innovative output leads to productivity growth.

These two seminal works have paved the way for the emergence of a relatively recent field of research aimed at analysing the peculiarities of the innovative process (both at macro and micro level) and its contribution to economic growth. In this respect, a distinction has to be made between those studies based on an application of a CDM fully structure model (i.e. that take into account all the three stages of the model) and those based on a CDM partial structure model (i.e. that consider at least one linkage between the three stages). Taking into account our main research aim, this work can be included in the latter category. Accordingly, in this brief survey we will focus on the two first stages of the CDM model, namely, the innovation inputs linked with their determinants, and the KPF.

Historically, due also to the lack of other measures of innovation, most studies have mainly focused their attention on the determinants of R&D activity, and its link with a measure of innovative output, most notably patents. However, such an approach appears to be oversimplified and too restrictive. In this respect in fact, as Stoneman (1995, p.5f.) suggests, "R&D is not the only source of technological improvement. A firm may generate its own technology through R&D. It may also generate technological advance through learning of various kinds, design, reverse engineering and imitation [….]. New process technologies may also be acquired from the suppliers of capital goods. The relevant importance of these different sources will depend upon the nature of the firm, its industrial sector and its technological base." Moreover, as pointed out by

Kleinknecht *et al.* (2002), R&D accounts just for a quarter of the total expense aimed at obtaining product innovation.

Turning the attention to the innovative output measures, as suggested by several studies, patents appear to be a very rough proxy of innovation for different reasons. Firstly, firms generally prefer other ways of protecting their innovation (see Levin *et al.*, 1987). Secondly, firms with different characteristics (i.e. small *vs* large) and operating in different sectors (i.e. high-tech *vs* low-tech) show a different propensity to patent (see Archibugi and Pianta, 1992; Patel and Pavitt, 1993). Finally, patents differ greatly in their importance.

Accordingly, in the recent years, thanks also to the availability of more comprehensive and precise innovation surveys, some authors have tried to extend the classic approach used to study the firms' innovative process including other measures of innovation activities. In this respect a notable example is the work of Conte and Vivarelli (2005) that can be seen as one of the first attempt to extend the classic approach of the KPF by considering, apart from R&D, also the important role played by the technological acquisitions (investment in new machinery and equipment, and external technology incorporated in licences, consultancies, and know-how) and their impact in determining different types of innovative outputs (product and process innovation). They found that R&D is strictly related to product innovation, while technological acquisition is crucial for process innovation. Moreover, their analyses also show that small firms and firms belonging to low-tech sectors are more oriented "to buy" instead of "to make" technology, while large firms and firms operating in the high-tech sectors are much more R&D based. This is in line with Santamaria *et al.* (2009) that find that the impact of non-R&D activities is particularly important in low and medium-tech firms. Similarly, Pellegrino *et al.* (2012), test an augmented KPF trying to detect some differences among firms of different age. The results of their analyses suggest that, although in-house R&D appears to be important in enhancing the propensity to introduce product innovation both in mature and young firms, innovation intensity in the group of young firms is mainly dependent on embodied technical change from external sources.

A common trait of the above-mentioned works is the fact that they focused just on one stage of the CDM model, that is the KPF. If on the one hand, this approach allows testing the relationship between different measures of innovative inputs and outputs at the same time, on the other hand, it completely ignores the process underlying the firm's innovative decision (i.e. the first stage of the CDM model). This aspect, linked to the way in which most of the data on innovation are collected (in particular CIS data) can compromise the reliability of the results[3]. Thus, the trade-off here is between applying an approach that leads to consistent results but that takes into account just one measure of innovative input (mostly R&D; classical CDM model approach), or ignoring possible sample selection problems in favour of a more detailed analysis of the firm's input-output innovative relationship.

Recently, some authors have proposed an approach that takes into account both these aspects. In this respect it is worth mentioning the work of Polder *et al.* (2010). More in detail, they estimate a CDM fully structure model considering two different measures of innovative input (R&D and the amount of investment in Information and communication technology (ICT)) and three different measures of innovative output (product, process and organizational innovation). They find a significant positive effect of ICT on the three measures of innovative output, while R&D turns out to be important

[3] The source of biased stems from a problem of sample selection that arises when the non-innovative firms are exclude from the analyses (for a more articulated discussion see Mairesse and Mohnen, 2010).

only to enhance the propensity to introduce product innovation. On the same line, Hall *et al.* (2012) further extend this approach considering two different measures of organizational innovation (organizational change associated with product and process innovation). Based on a large unbalanced panel of Italian manufacturing firms, they find that both R&D and ICT are important drivers of innovation activity, although R&D appears to be more relevant for product and process innovation.

In the spirit of these contributions, in this work, as previously mentioned, we rely on an extension of a CDM partial structure model including investments in TA as an additional innovation input besides R&D, and two different measures of innovative outputs (product and process innovation). To the best of our knowledge, this is one of the first studies to include in a CDM type-model an indicator of technological acquisition. Moreover, as another important element of novelty, we analyse the existence of possible differences between mature and young firms (see Section 4 for a more precise definition of these two categories) in terms of both drivers of R&D and TA and peculiarities of the KPF. In this respect, no existing literature has provided evidence to these particular research questions. However, some interesting and useful insights can be gained by considering the main results of some recent studies that have looked at the peculiarities of the young companies' innovative process.

Garcia-Quevedo *et al.* (2011), drawing on an unbalanced dataset of more than 2,000 Spanish manufacturing firms, look at the R&D drivers of young and mature firms. The results of their econometric estimations show that different firms and market characteristics play a different role in determining the innovative decisions of mature and young firms. In particular, if on the one hand factors like market concentration and the degree of product diversification are more important in fostering the innovative activity of the mature firms only, on the other hand young firms' spending on R&D

seem to be more sensitive to demand pull variables, suggesting the presence of credit constraints for this particular type of firms.

In a very recent study, Criscuolo *et al.*(2012), unlike the above mentioned study, concentrate their attention to the output side of the innovative activity. In particular, using a large sample of UK firms, they try to explore possible differences between start-ups and established firms in terms of innovative performance, looking at both manufacturing and service sectors. They find that being a new firm increase the probability to introduce a radical product or process innovation in the service sector, while in the manufacturing sectors new established firms tend to be less innovative than established firms. This latter result is in line with the previously mentioned study of Pellegrino *et al.* (2012) that, relying on data from the Italian CIS, show that the young innovative companies are less R&D based and perform worse in terms of innovative turnover than their mature counterparts.

3. Model and Econometric Methodology

As mentioned in the Introduction, the empirical analyses of this work are carried out by applying an extended version of a classic CDM partial structure model. More in detail, we follow an approach initially proposed by Griffith *et al.* (2006) and subsequently used also by Mairesse and Robin (2009) who enrich the basic CDM model considering as innovative outputs product as well as process innovation[4]. We augment their model including a further equation for technological acquisition. Accordingly, our

[4] Both studies are based on a fully structure CDM model.

approach is formalised in 6 equations: (1) the firms' decision to engage in R&D activity; (2) the firm's decision regarding the amount of resources to be invested in R&D activity; (3) the firms' decision to invest in TA; (4) the firm's decision regarding the amount of resources to be invested in TA; (5) – (6) the knowledge production function, in which we consider two different innovative outputs (product and process innovation).

Another important peculiarity of our empirical strategy is that, in contrast to most previous studies, we do not focalise our attention only on the cohort of innovative firms, but perform our analysis considering the whole sample of firms. In particular, the KPF (steps (v-vi)) is estimated using the predicted values for all firms obtained from the estimations of steps (i) - (iv) that are based on reported R&D and TA figures. This approach reflects the assumption that all the firms exert some effort in innovative activities, although some of them do not report any innovative investment. In this respect, firm' workers may spend a certain amount of their workday trying to find out a more efficient way to carry out the production process in which they are involved. The same process could apply for personnel employed in other firms that provide external technology (investment in new machinery and equipment and purchasing of external technology incorporated in licences, consultancies and know-how). In both cases if the effort does not exceed a certain threshold will not be reported by the firm as investment in R&D activity and TA.

Having delineated the main peculiarities of our empirical strategies, in the following two subsections we fully describe the econometric methodologies and the specifications used for the estimations of the 6 equations of the model.

3.1 Innovation inputs: R&D and technological acquisitions

We individuate two different types of innovation inputs: R&D expenditures (both *intramural* and *extramural*) and technological acquisitions (both in their embodied and disembodied component). As it is well known in the empirical literature dealing with CIS survey (see discussion in Section 4), these variables are subject to selectivity: only those firms that have claimed to be involved in product or process innovation (completed/ongoing/abandoned) report data on innovative investments. Furthermore, since that both types of innovative activities can be performed in an informal way these two variables may be also censored. However, as explained in the previous section, if this innovative effort does not reach a certain threshold the firm will not report it as expenditure. Consequently, both the variables are made up of a certain number of zero and missing values. Econometrically, this mixed pattern of zero/missing and positive values naturally leads to a tobit II model (see Amemiya, 1984) defined as follows.

Let i=1,..........,N index firms. The two firm's innovative decisions are defined by the two binary variables $\mathrm{RDT\_d_i}$ and $\mathrm{TAT\_d_i}$ that take value 1 when R&D and TA respectively are observed and 0 otherwise. We linked $\mathrm{RDT\_d_i}$ and $\mathrm{TAT\_d_i}$ with the two latent variables $\mathrm{RDT\_d_i^*}$, $\mathrm{TAT\_d_i^*}$ such that:

$$(1)\mathrm{RDT\_d_i} = \begin{cases} 1 \text{ when } & \mathrm{RDT\_d_i^*} = \alpha_1' \mathrm{x_{1i}} + \varepsilon_{1i} > 0 \\ 0 \text{ when } & \mathrm{RDT\_d_i^*} = \alpha_1' \mathrm{x_{1i}} + \varepsilon_{1i} \leq 0 \end{cases}$$

and

$$(2)TAT\_d_i = \begin{cases} 1\, when & TAT\_d_i^* = \alpha_2' x_{2i} + \varepsilon_{2i} > 0 \\ 0\, when & TAT\_d_i^* = \alpha_2' x_{2i} + \varepsilon_{2i} \leq 0 \end{cases}$$

We indicate with RDT_i the amount of firm's turnover employed as investment in both *intramural* and *extramural* R&D, and with TAT_i the amount of firm's turnover employed as investment in technological acquisitions. Denoting the correspondent latent variables with RDT_i^* and TAT_i^* we have:

$$(3)\, RDT_i = \begin{cases} RDT_i^* = \beta_1' w_{1i} + u_{1i} & \text{when } RDT\_d_i = 1 \\ 0 \quad \text{when} \quad RDT\_d_i = 0 \end{cases}$$

and

$$(4)\, TAT_i = \begin{cases} TAT_i^* = \beta_2' w_{2i} + u_{2i} & \text{when } TAT\_d_i = 1 \\ 0 \quad \text{when} \quad TAT\_d_i = 0 \end{cases}$$

For each firm i, x_j and w_j (with j = {1, 2}) are vectors of explanatory variables some of which could be common to both vectors. Assuming that each pair of error terms ε_1 and u_1, and ε_2 and u_2 is bivariate normally distributed with correlation coefficients $\rho_{\varepsilon 1u1}$ and $\rho_{\varepsilon 2u2}$, we estimate equations (1) - (3) and (2) - (4) with the Heckman two-step procedure (Heckman, 1979).

Since that our analysis is focused on the whole sample of firms and not only on that of innovative firms, to model the firms' innovative decisions (equations (1) and (2)) we can only use the limited information available for all firms (see next section). Taking into account this important aspect, and bearing in mind the primary objective to make fully comparable the microdata stemming from CIS3 and CIS4 datasets, the choice of the explanatory variables has been made following both the original framework proposed by Crépon *et al.* (1998) and the extensions put forward by Griffith *et al.* (2006) and Mairesse and Robin (2009). For sake of symmetry, we decided to estimate the 2 pair of equations (equations (1)-(3) and (2)-(4)) using the same specifications.

Starting from the selection equations (1) and (2), we use an indicator whether the firm is part of an enterprise group or not, indicator of whether the international market is the firm's most significant market in order to measure the international competition and two indicators of whether the firm makes use respectively of patents and strategic methods (registration of design, trademarks, copyrights) to protect its innovations[5]. Moreover, following the Schumpeterian tradition we include a set of industry dummy variables (based on the 2-digit ateco codes[6]) to capture the market conditions and a variable reporting the log of the total number of employees as measure of firm size.

To model the firms' propensity to invest in R&D and TA (equations (3) and (4)) we can rely on additional information that are available only when firms are innovative and that may be, consequently, useful to characterize the R&D/TA (see discussion in Section 4). Along with the regressors used in the selection equations, in accordance with previous evidence that show the important role of cooperation agreements in affecting the level of investment in innovative activities (Cassiman and Veuglers, 2002; Piga and Vivarelli, 2003, 2004), we also consider a dummy variable that identifies firms that had some cooperative agreements on innovation activities during the three-year period. Moreover, in order to test the supposed positive impact of the public funding in fuelling the firm' innovative activity (see Busom, 2000; Gonzales *et al*., 2005) a binary variable indicating if the firm has received some (local/national/EU) public financial supports for innovative activities is included. In addition, we also consider two binary variables that take on value 1 if the firm has used respectively any type of internal and external

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[5] Previous studies generally show a clear cut positive link between these factors and the firms' innovative activity (see Levin *et al.*, 1987; Salomon and Shaver, 2005; Liu and Buck, 2007; Raymond *et al.* 2009).

[6]The Italian industrial classification (Ateco codes) corresponds, to a large extent, to the European NACE taxonomy.

sources of information for its innovative activity. In this respect, a recent stream of literature emphasises the important role played by both internal and external sources of information in determining the innovative choice of a firm (see Amara and Landry, 2005).

For reasons of identification the employed econometric method requires an exclusion restriction. Accordingly, we decide to exclude from equations (3) and (4) the variable firm size and the variable that indicates if the international market is the firm's most significant market. As for the first variable, the choice was primarily motivated by the fact that the dependent variables, being expressed in intensities, are implicitly scaled for size, and it is further supported by the results of previous studies. In this respect, for example, Griffith *et al.* (2006) find that in several European countries firm size affects significantly the probability to engage in R&D but not the level of R&D investment. Similarly, several contributions have shown a positive and significant causal effect of different indicators of international competition on the firm's probability to innovate but not on the level of investment of R&D activities (see Salomon and Shaver, 2005; Griffith *et al.* 2006; Liu and Buck, 2007).

4.2 Innovation outputs: product and process innovation.

In this study, we model the KPF considering two types of innovative outputs, that is process and product innovations. Formally, the following two equations can be written as follows:

$$(5)\ \ \mathrm{PROD}_i^* = \alpha_3'\widehat{\mathrm{RDT}}_i + \beta_3'\widehat{\mathrm{TAT}}_i + \gamma' x_{3i} + \varepsilon_{3i}$$

$$(6)\ \mathrm{PROC}_i^* = \alpha_4'\widehat{\mathrm{RDT}}_i + \beta_4'\widehat{\mathrm{TAT}}_i + \pi' x_{4i} + \varepsilon_{4i}$$

Where $\widehat{\mathrm{RDT}}_{\mathrm{i}}$ and $\widehat{\mathrm{TAT}}_{\mathrm{i}}$ represent the predictions of the dependent variables of equations (3) and (4) conditional on the firm' decision to engage in innovation activities. Also in this case, we do not observe the level of knowledge generated by the firm, but we only have information on whether the firm has realised product and/or process innovation. Accordingly, if we indicate with $\mathrm{PROD_i}$ and $\mathrm{PROC_i}$ the two dummy variables that single out the realization of these events we will have:

$$\text{(5a)}\ \Pr[\mathrm{PROD_i} = 1] \quad = \Pr\left[\alpha_3' \,\widehat{\mathrm{RDT}}_{\mathrm{i}} + \beta_3' \widehat{\mathrm{TAT}}_{\mathrm{i}} + \gamma' \mathrm{x}_{3\mathrm{i}} + \varepsilon_{3\mathrm{i}} > 0\right]$$

$$\text{(6a)}\ \Pr[\mathrm{PROC_i} = 1] \quad = \Pr\left[\alpha_4' \,\widehat{\mathrm{RDT}}_{\mathrm{i}} + \beta_4' \widehat{\mathrm{TAT}}_{\mathrm{i}} + \pi' \mathrm{x}_{4\mathrm{i}} + \varepsilon_{4\mathrm{i}} > 0\right]$$

Assuming that the two error terms $\varepsilon_{3\mathrm{i}}$ and $\varepsilon_{4\mathrm{i}}$ follow a bivariate normal distribution and that are correlated with correlation coefficient $\rho_{\varepsilon_{34}}$ equation (5) and (6) define a bivariate Probit model, and are jointly estimated by maximum likelihood in Stata.

Apart from firm size (expressed in logarithm) and the set of industry-specific dummies, the vectors γ and π include 2 dummies denoting those firms that have realised managerial, strategic or organisational innovation ('IORG'), and those that have implemented changes in marketing concepts or strategies ('IMARK'). In this respect, the occurrence of other forms of innovation should be complementary to the two innovative inputs considered in the specification (see Bresnahan *et al.*, 2002; Hitt and Brynjolfsson, 2002; Piva *et al.*, 2005).

As already stated, by using the predictions for innovation inputs instead of the reported values we are able to estimate the knowledge production function using the whole sample. In this way, the number of observations is increased and the selectivity bias is avoided. Moreover, as long as the variables in equations (1)-(3) and (2)-(4) are exogenous, such approach allows us to control for possible endogeneity of the innovative inputs. In this respect, it is very likely that unobservable characteristics included in the error terms ε_{3i} and ε_{4i} are important in increasing both the firms' innovative effort and the firms' propensity to introduce new innovations. This would cause an upward biased estimate of the parameters α_3, β_3 and α_4, β_4 because of their positive correlation with ε_{3i} and ε_{4i} respectively.

4. Data

This work uses firm-level data drawn from the third and fourth (CIS3 and CIS4) waves of the Italian CIS. The CIS is a harmonized survey that is carried out by national statistical agencies (ISTAT in Italy) in all the 27 EU member States under the coordination of Eurostat. CIS3 was conducted in 2001 and provides information for the three-year period 1998-2000, while CIS4 was conducted in 2005 and provides information for the three-year period 2002-2004. These surveys are representative at both sector and firm size level of the entire population of Italian firms with more than

10 employees. In conducting the surveys, ISTAT adopts a weighting procedure that relates the sample of firms interviewed to the entire population[7] (ISTAT, 2004).

As previously mentioned, the way in which the Italian CIS questionnaire is structured allows us to have only a limited amount of information regarding all the interviewed firms. In particular, all firms are requested to answer to some questions providing general information, such as the number of employees, the main industry of affiliation, the belonging to a group and whether they have innovation activities (completed/ongoing/abandoned) or not. Only those firms that declare to be innovative are asked to answer to a much larger set of additional questions on the firms' innovativeness, the effects of innovation, participation in cooperative innovation activities and access to public funding, among the others. Most of these information are available in both datasets, although some differences between the two questionnaires can be detected. More in detail, with respect to the variables that we have used for the estimations, while CIS3 gathers several information regarding the formal methods of protection for innovation, CIS4 provides information only on whether a firm has applied or not for a patent.

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[7] Firm selection was carried out through a 'one step stratified sample design'. The sample in each stratum was selected with equal probability and without reimmission. The stratification of the sample was based on the following three variables: firm size, sector, regional location. Technically, in the generic stratum h, the random selection of n_{h} sample observations among the N_{h} belonging to the entire population was realized through the following procedure:
- a random number in the 0-1 interval was attributed to each N_h population unit;
- N_h population units were sorted by increasing values of the random number;
- units in the first n_h positions in the order previously mentioned were selected.

Estimates obtained from the selected sample are very close to the actual values in the national population. The weighting procedure follows Eurostat and Oslo Manual (OECD, 1997) recommendations: weights indicate the inverse of the probability that the observation is sampled. Therefore, sampling weights ensure that each group of firms is properly represented and correct for sample selection. Moreover, sampling weights help in reducing heteroskedasticity commonly arising when the analysis focuses on survey data. It is important to note that this sample weighting was carried out *ex-ante* by ISTAT in the process of providing the original data, therefore it is not implying any cleaning procedure by the authors.

The original CIS3 and CIS4 database were made up of respectively 15,512 (CIS3) and 21,854 (CIS4) firms operating in all the sectors of economy. After dropping those firms not operating in the manufacturing sectors, those that employ more than 5,000 employees and that state a level of R&D expenditures and/or TA higher than 50% of the total turnover we ended up with 7,185 (CIS3) and 7,329 (CIS4) innovating and not-innovating firms.

According to the particular aim of this paper it has been necessary to single out a given age threshold in order to select from the total samples the two sub-samples of young and mature firms. In line with previous works (see Garcia-Quevedo *et al.* 2011 and Pellegrino *et al.* 2012) and following the general criteria that the European Commission used to single out the YICs, we opted for 8 years threshold[8]. Table 1 shows the sectoral composition of the total sample distinguish between young and mature firms. The overall impression is that no striking differences emerge with respect to the distribution among the various samples (both total samples and sub-sample of young and mature firms) across the different industries categories[9]. As far as size is concerned, young firms in CIS3 appear to be much smaller than both their mature counterparts (56 *vs* 90 employees on average), and the group of young firms in CIS4 (56 *vs* 98

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[8] According to the European Commission's State Aid rules, Young Innovative Companies are defined, among other requirements, as companies with less than 6 years. However some European countries in adopting the European Directive have extended this threshold (i.e. 8 years for France and Estonia). The choice of 8 years allows us to reach a good degree of representativeness of the sub-sample of young firms, without increasing the age threshold too much. However we performed several robustness checks, assuming the alternative thresholds of 6, 7, 9 and 10 years; results – available upon request – are consistent, both in terms of sign and statistical significance of the estimated coefficients, with those discussed in Section 5.

[9] To aggregate the industry categories, based on the 2-digit NACE classification, we follow Griffith *et al.*(2006)

employees on average). This aspect, due to the different composition of the two datasets, does not affect the reliability of the econometric estimations[10].

< INSERT TABLE 1 >

Table 2 gives the summary statistics (mean and standard deviation) for the dependent variables and the regressors used in the model (see table A1 in the appendix for a detailed definition of the variables). Also in this case, CIS3 and CIS4 samples look very similar in average, the only notable difference being in the higher percentage of CIS3's firms introducing product innovation (28% *vs* 19%). However looking at the two sub-samples of young and mature firms, more evident differences can be detected. In particular, young firms appear to be less innovative with respect both the intensity of the innovative effort and the capacity to realise process and product innovations. Furthermore, it seems that the use of appropriability means (both formal and strategic) increase with age, as well as the degree of international market exposure.

< INSERT TABLE 2 >

[10] Robustness checks were performed used a CIS4 sample cleaned by potential outliers as far as young firms are concerned. The results –available upon request– are in line (both in terms of sign and statistical significance) with those discussed in Section 5.

5. Results

In the following two sub-sections we comment the estimation results of the 6 equations model outlined in Section 3. More in detail for each step of the model we present the results for the entire samples (CIS3 and CIS4) and for the four sub-samples of mature incumbents and young firms. Accordingly, in discussing the results, we will consider possible differences both among sub-samples of firms belonging to different datasets and between mature and young firms belonging to the same dataset.

Before moving to the discussion, it is important to note that our estimations are based on cross-sectional data, and most of the regressors used are simultaneously determined. Bearing in mind this important caveat, the interpretation of the results has to be done with caution.

5.1 Innovation inputs

Tables 3 and 4 show the estimation results for respectively the R&D – (1) and (3) –, and TA – (2) and (4) – equations. We first concentrate our attention on possible differences regarding the role played by factors in determining the innovate choice (R&D and TA) of the firms both in terms of whether or not to engage in innovative activities and how intensively invest in the same innovative activities. More in detail, we will look at the results of the selection and main equations for the two different innovative inputs (R&D and TA) concentrating the attention only to the total samples of the two datasets (columns 1 – 2 and 7 – 8 in table 3 and 4).

A first notable result is that, in general, the sign and the significance of the coefficients are quite similar across the two different datasets. This means that our results are robust across different samples of firms over different time periods. If we compare the results of the two input equations, the most evident difference is related to the level of significance of the variable ‘COOP’. Indeed, it appears that those firms that take part into cooperative activities are more likely to increase the intensity of their investment in R&D activities but not in TA. This result could reflect the vital role played by some cooperation partner (in particular universities, private and public research institutes) in determining the firm’ R&D effort. Apart from this result, no other relevant differences can be detected between the two equations. In particular, looking at the other factors that are exclusively included in the level equations, the use of any type of sources of information to innovation (both internal and external) turns out to be insignificant in determining the firms’ level of investment in both innovative inputs categories. On the contrary, there appears that those firms that benefit from any type of support to their innovation activities are more likely to spend more on R&D and TA.

As for the factors included in both selection and level equations, we can see that being part of a group does not seem to be an important driver of neither R&D nor TA activities. Indeed, the coefficients of the variable ‘IG’, with the exception of the R&D selection equation refers to the CIS4 (column 7 in table 3) turns out to be insignificant in all the models. On the contrary, those firms that have made use of appropriability means (both formal and strategic), seem to have more chance to engage in both types of innovative activities. Moreover, the formal methods to appropriability (variable ‘PATDEP’) appear to have an important role also in enhancing the level of investment in both R&D and TA.

Finally, looking at those variables included only in the selection equations, we can see that larger firms, and firms that are more oriented towards international markets are also more likely to engage in both innovation activities.

We now move to the comparison between mature and young firms. In particular, we will describe the estimations results of the remaining columns (3 – 4 – 5 – 6 – 9 – 10 – 11 and 12) in tables 3 and 4.

Firstly, also in this case, with the exception of some slight differences (i.e. variable 'COOP' in the R&D equation significant for the sample of CIS4 young firms but not for their CIS3 counterparts), the results are pretty much consistent across the different samples/sub-sample of firms over different time periods. Moreover, looking at the two different sub-samples of mature and young firms, some results are in line with those regarding the total samples. More in particular, the variable 'IG', with the exception of the selection equation in CIS4 (where the coefficient is positive and slightly significant), does not affect the two different firm innovative decisions. Furthermore, firm size and the international market exposure appear to be important factors in boosting the firm's probability to engage in both R&D and TA, regardless the age of the firms[11]. In addition, both mature and young firms (even if this evidence is stronger for mature firms) that cooperate on innovation activity are likely to spend more on R&D but not on TA. Moreover, in line with the previously discussed results, the variable 'SUPPORT' appears to play an important role in determining the level of R&D investment in both sub-sample and for both datasets. However, this variable turns out to be still highly significant in the TA equations, for sample of mature firms only. This result, which holds across the two different datasets, could suggest the need to design different policy measurers to support different innovative activities (R&D *vs* TA) of different cohorts of firms (mature *vs* young). Another important difference in terms of relevance of innovative drivers between the two sub-samples is related to the sign and

[11] The only result that appears in contrast regards the insignificance of the variable EXP_d in the TA equation for the sample of young firms belonging to CIS3.

significance of the two dummy variables denoting those firms that make use of any type of internal and external sources of information for innovation activities. Looking at the R&D equation, in fact, in both the dataset the role of the variable 'INFO_IN' is highly important in boosting the intensity of the investment of young firms, but appears not relevant in the case of mature firms. As for the variable identifying those firms that make use of external sources of information for their innovation activities, as can be seen from table 3, young firms in CIS3, in contrast to their mature counterparts, seem to be negatively affected by this factor with respect to their R&D intensity decision. Instead, turning the attention to the TA equation (table 4), this variable appears to significantly increase the level of investment in TA among young firms, but not among mature ones[12]. All in all, these important evidence suggest that: 1) young firms tend to show an higher level of sensitivity to the different sources of information to innovation with respect to their mature counterparts when they have to decide how much invest in innovative activities (both R&D and TA); 2) different sources of information (internal *vs* external) have a distinct impact in determining the level of investment in R&D and TA as far as young firms are concerned.

Finally, as for the means of appropriability, if the variable 'PROT' (strategic method of protection) have almost no impact on the amount of firm's innovative investments, the use of formal methods of protection (variable 'PATDEP') turns out to be highly significant in both main equations and across the two datasets for the mature firms only.

Both the high values of the correlation coefficients (Rho) between the selection and the main equations and the statistical significance of the Lambda Mills ratio in 11

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[12] This result holds true only with reference to CIS3.

out of 12 models (see lower part of table 3 and 4) confirm the validity of the choice of this Heckman-Type specification.

< INSERT TABLE 3 AND 4 >

5.2 Innovation outputs

Table 5 reports the econometric results of the KPF considering both product and process innovation. More in detail, as for the two input equations we report the results for the three different samples (total, mature and young) for both CIS3 (first 6 columns) and CIS4 datasets (last 6 columns). The numbers reported are marginal effects evaluated at the sample means. The use of predicted variables ($\widehat{TAT}$ and $\widehat{RDT}$) as regressors makes the usual standard errors invalid. Accordingly, in table 5 we report the t-statistics calculated using the bootstrapped standard errors that appears to be larger than the usual ones.

Following the structure of the previous subsection, we first concentrate the attention on the general results (total samples) and then on possible differences between mature and young firms.

The first important result is that, in line with most of the related literature (see Section 2), R&D appears to be more important for product innovation than for process innovation. This result is particularly evident with respect to CIS4. As can be seen in fact (columns 7 – 8), the effect of the variable $\widehat{RDT}$ is highly significant for product innovation and insignificant for process innovation. Instead, this evidence in less clear in CIS3 where the impact of the variable is equally statistically significant for both innovative outputs. However, as can be seen, the magnitude of its effect is much stronger on product than on process innovation (0.81*vs* 0.33).

On the other hand, investment in TA is important for both types of innovation and in both CIS3 and CIS4 samples, the variable $\widehat{\mathrm{TAT}}$ being always highly significant. However, looking at the magnitude of marginal effects, we can see that this particular innovative input appears to be more important for process innovation.

Briefly looking at the other results, we notice that the two dummies variables ('IORG' and 'IMARK') identifying those firms that have realised 'wider' innovation activities, turn out to be always positive and significant, with the variable 'IMARK' appearing more important for product innovation. This result is in line with our expectations, since that the implementation of the marketing concepts is more related to the realisation of product innovation than process innovation.

Finally, the sign and the level of significance of the marginal effects of the variable 'LSIZE' suggest us that larger firms are more likely to engage in both product and process innovations.

Turning our attention to the 4 sub-samples of young and mature firms, the overall impression is that the estimates results are pretty much in line with those previously discussed for both groups of firms. The only notable evidence is represented by the fact that the variable $\widehat{\mathrm{RDT}}$ in one case (CIS4 dataset) is important in increasing the likelihood of process innovation for the young firms only. This result could be related to the fact that young firms, being less experienced than their mature counterparts and possibly less specialised with respect to their innovative process, are more able to exploit the interaction between different innovative inputs to pursue at the same time the realisation of different innovative outputs. However, this speculation is not fully supported by our results, since the evidence on which is based does not hold true for the CIS3 dataset. In this case, in fact the variable $\widehat{\text{RDT}}$ appears to be highly significant for both mature and young firms.

As far as the impact of the variable $\widehat{\text{TAT}}$ is concerned, looking at the estimation results, it is quite evident that the level of investment in TA is equally important for both types of innovations without any particular difference between mature and young firms. Again the impact of this variable appears to be more important in determining the realisation of process innovations, and this is particularly evident with respect to the CIS4 sample. Similarly, the marginal effects and the level of significance of the remaining variables (‘IORG’, ‘IMARK’ and ‘LSIZE’) are in line with those of the total sample. Also in this case, for both young and mature firms the realisation of changes in marketing or strategies (variable ‘IMARK’) is more important for product than for process innovation.

Finally, from the lower part of table 5 emerge clearly that the two equations are always highly correlated via the errors terms, the level of the rho ranging between 0.46 and 0.74. This aspect, which suggests the existence of a certain degree of complementarities between the two firms’ innovative outputs supports the adoption of a Biprobit model.

< INSERT TABLE 5 >

6. Conclusion

Based on an extension of a traditional partial structure CDM model, this paper has analysed the determinants of the firms' innovative effort and the results of this effort in terms of innovative outputs by looking at R&D/TA and PROC/PROD and by distinguishing between mature and young firms. Using data from the third and fourth Italian Community Innovation Survey we estimate a structural model that allows for the fact that some firms may undertake innovation but do not report it as R&D and/or TA. We find some interesting results that are robust across different samples of firms over different time periods:

1) Looking at the impact of the different drivers in determining the firms' decision to innovate or not in R&D and TA, no particular differences between mature and young firms can be detected. More in detail, apart from the variable denoting those firms that belong to an industrial group, all the other factors (appropriability conditions, international market exposure and size) turn out to be important in increasing the probability to invest both in R&D and TA for both sub-samples of firms.
2) Different firm and market characteristics have a different impact in affecting the level of investment in R&D/TA both in general and for mature and young firms. In this respect, if the variable SUPPORT plays an important role in increasing the level of investment in R&D in both sub-samples and for both datasets, in the TA equation this variable turns out to be still highly significant only for the group of mature firms. Another important result is related to the fact that young firms show a higher level of sensitivity to the internal and external sources of innovation with respect to their mature

counterparts when they have to decide how much invest in the two innovative inputs. Moreover, it seems that these two different sources of information have a distinct impact in determining the level of investment in R&D and TA as far as young firms are concerned. Finally, the variable that indicate the use of formal methods of protection of innovation activities turns out to be highly significant in both R&D and TA equations and across the two datasets for the mature firms only.

3) No particular differences between young and mature firms emerge in the KPF. Although R&D and TA appear to be both important in increasing the likelihood to introduce both product and process innovation, looking at the marginal effects, there appears that R&D is more linked to product innovation, while TA with process innovation.

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Table 1. Sectoral composition (2-digit manufacturing sectors) and average employment; all firms - mature firms; young firms (CIS3 - CIS4)

	CIS3						CIS4					
	TOT		MATURE		YOUNG		TOT		MATURE		YOUNG	
	N	%	N	%	N	%	N	%	N	%	N	%
Food	492	6.9	446	7.2	46	4.9	638	8.7	550	9.2	88	6.6
Textile	1,191	16.6	995	16.0	196	20.7	1,172	16.0	895	15.0	277	20.7
Wood/Paper	986	13.7	882	14.1	104	11.0	907	12.4	756	12.6	151	11.3
Chemicals	494	6.9	435	7.0	59	6.2	460	6.3	382	6.4	78	5.8
Plastic/Rubber	415	5.8	361	5.8	54	5.7	310	4.2	266	4.4	44	3.3
Non-metallic Min.	471	6.6	414	6.6	57	6.0	504	6.9	432	7.2	72	5.4
Basic metals	853	11.9	741	11.9	112	11.8	1,306	17.8	1,054	17.6	252	18.8
Machinery	551	7.7	483	7.8	68	7.2	566	7.7	472	7.9	94	7.0
Electrical	826	11.5	700	11.2	126	13.3	671	9.2	544	9.1	127	9.5
Vehicles	395	5.5	325	5.2	70	7.4	364	5.0	286	4.8	78	5.8
Misc.	511	7.1	454	7.3	57	6.0	431	5.9	351	5.9	80	6.0
Total	7,185	100	6,236	100	949	100	7,329	100	5,988	100	1,341	100
Av. Emp.	85		90		56		102		102		98	

Table 2. Descriptive statistics: mean and standard deviation of the variables; all firms- mature firms- young firms (CIS3 –CIS4)

	CIS3			CIS4		
	TOT	MATURE	YOUNG	TOT	MATURE	YOUNG
RDT_d	0.21 (0.41)	0.22 (0.41)	0.15 (0.36)	0.25 (0.44)	0.26 (0.44)	0.22 (0.41)
RDT	0.048 (1.78)	0.049 (1.79)	0.041 (1.75)	0.066 (2.42)	0.067 (2.43)	0.061 (2.36)
TAT_d	0.29 (0.45)	0.30 (0.46)	0.21 (0.41)	0.34 (0.47)	0.34 (0.47)	0.30 (0.46)
TAT	0.011 (3.70)	0.011 (3.63)	0.011 (4.15)	0.012 (3.76)	0.012 (3.67)	0.013 (4.13)
PROD	0.28 (0.45)	0.29 (0.45)	0.23 (0.42)	0.19 (0.39)	0.19 (0.40)	0.17 (0.38)
PROC	0.29 (0.45)	0.30 (0.46)	0.25 (0.43)	0.30 (0.46)	0.31 (0.46)	0.28 (0.45)
IG	0.18 (0.38)	0.18 (0.39)	0.17 (0.37)	0.23 (0.42)	0.23 (0.42)	0.23 (0.42)
PATDEP	0.12 (0.32)	0.12 (0.33)	0.08 (0.27)	0.12 (0.32)	0.12 (0.33)	0.09 (0.29)
PROT	0.21 (0.41)	0.22 (0.41)	0.15 (0.35)	0.18 (0.39)	0.19 (0.39)	0.15 (0.36)
COOP	0.05 (0.23)	0.06 (0.23)	0.04 (0.19)	0.06 (0.24)	0.06 (0.24)	0.06 (0.24)
SUPPORT	0.20 (0.40)	0.21 (0.40)	0.16 (0.36)	0.18 (0.38)	0.18 (0.39)	0.15 (0.36)
INFO_IN	0.13 (0.33)	0.13 (0.34)	0.09 (0.29)	0.14 (0.35)	0.14 (0.35)	0.12 (0.33)
INFO_EX	0.18 (0.38)	0.19 (0.39)	0.13 (0.33)	0.20 (0.40)	0.20 (0.40)	0.19 (0.39)
EXP	0.66 (0.47)	0.68 (0.47)	0.58 (0.49)	0.53 (0.50)	0.55 (0.50)	0.43 (0.50)
LSIZE	3.64 (1.09)	3.69 (1.10)	3.33 (0.94)	3.67 (1.15)	3.71 (1.15)	3.50 (1.15)
IORG	0.47 (0.50)	0.47 (0.50)	0.45 (0.50)	0.35 (0.48)	0.35 (0.48)	0.34 (0.47)
IMARK	0.47 (0.50)	0.47 (0.50)	0.42 (0.49)	0.21 (0.41)	0.22 (0.41)	0.20 (0.40)
Obs	7,185	6,239	949	7,329	5,988	1,341

Standard deviation in brackets

Table 3. Estimation results for the R&D equations (CIS3 - CIS4)

	CIS3						CIS4					
	TOT		MATURE		YOUNG		TOT		MATURE		YOUNG	
Dep. Var.	RDT_d	RDT	RDT_d	RDT	RDT_d	RDT	RDT_d	RDT	RDT_d	RDT	RDT_d	RDT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IG	0.04	-0.02	0.03	0.02	0.16	-0.61	0.13***	-0.03	0.12**	-0.16	0.21*	0.62
	(0.78)	(-0.08)	(0.48)	(0.09)	(1.01)	(-0.76)	(2.83)	(-0.12)	(2.28)	(-0.64)	(1.68)	(0.98)
PATDEP	0.70***	1.08***	0.67***	1.00***	0.95***	1.04	0.73***	1.51***	0.66***	1.47***	1.17***	1.20
	(11.23)	(3.93)	(10.32)	(3.56)	(4.27)	(0.92)	(12.55)	(4.72)	(10.63)	(4.37)	(7.17)	(1.31)
PROT	0.35***	0.39*	0.35***	0.42*	0.34*	-0.08	0.29***	0.46*	0.30***	0.32	0.27**	1.26*
	(6.77)	(1.69)	(6.42)	(1.77)	(1.84)	(-0.09)	(6.04)	(1.87)	(5.61)	(1.23)	(2.08)	(1.94)
COOP		0.86***		0.94***		-0.07		1.16***		0.90***		2.37***
		(4.18)		(4.42)		(-0.10)		(4.98)		(3.57)		(4.13)
SUPPORT		1.26***		1.12***		2.91***		0.90***		0.76***		1.43***
		(7.92)		(6.72)		(5.23)		(4.82)		(3.79)		(3.17)
INFO_IN		0.19		0.08		1.61***		0.25		0.05		1.09**
		(1.16)		(0.48)		(2.79)		(1.32)		(0.25)		(2.43)
INFO_EX		0.06		0.15		-1.15**		-0.05		-0.01		-0.53
		(0.36)		(0.87)		(-2.07)		(-0.30)		(-0.05)		(-1.16)
EXP	0.41***		0.42***		0.30**		0.48***		0.47***		0.55***	
	(7.90)		(7.56)		(2.21)		(11.94)		(10.57)		(5.52)	
LSIZE	0.33***		0.33***		0.29***		0.23***		0.24***		0.20***	
	(15.45)		(14.67)		(4.39)		(12.07)		(11.33)		(4.22)	
_cons	-2.73***	-3.00***	-2.83***	-2.93***	-2.02***	-2.32	-2.21***	-2.78***	-2.23***	-2.16***	-2.16***	-4.77**
	(-24.97)	(-4.64)	(-23.89)	(-4.30)	(-6.62)	(-1.18)	(-24.12)	(-3.77)	(-22.28)	(-2.73)	(-9.10)	(-2.57)
Lambda	2.34***		2.29***		1.84		2.20***		1.90***		3.20***	
	(7.09)		(6.66)		(1.51)		(5.46)		(4.34)		(3.34)	
Rho	0.66		0.66		0.57		0.52		0.46		0.73	
N	7,185	1,513	6,236	1,366	949	147	7,329	1,859	5,988	1,565	1,341	294

t- statistics in brackets: * Significant at 10%; **5%;***1%. All regressions include industry dummies (results available upon request).

Table 4. Estimation results for the Technological Acquisitions equations (CIS3- CIS4)

	CIS3						CIS4					
	TOT		MATURE		YOUNG		TOT		MATURE		YOUNG	
Dep. Var.	TAT_d	TAT	TAT_d	TAT	TAT_d	TAT	TAT_d	TAT	TAT_d	TAT	TAT_d	TAT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IG	-0.05	-0.43	-0.06	-0.35	0.05	-0.42	0.07	0.17	0.07	-0.01	0.05	0.60
	(-1.04)	(-1.20)	(-1.17)	(-0.94)	(0.34)	(-0.26)	(1.49)	(0.50)	(1.42)	(-0.04)	(0.45)	(0.59)
PATDEP	0.45***	1.23**	0.41***	1.20**	0.88***	2.25	0.42***	1.49***	0.37***	1.20***	0.71***	3.05*
	(7.53)	(2.39)	(6.55)	(2.38)	(4.12)	(0.69)	(7.51)	(3.24)	(6.15)	(2.63)	(4.70)	(1.86)
PROT	0.34***	0.32	0.37***	0.38	-0.01	-0.19	0.32***	0.97**	0.32***	0.87**	0.30**	0.56
	(7.21)	(0.72)	(7.44)	(0.83)	(-0.03)	(-0.10)	(7.05)	(2.45)	(6.51)	(2.16)	(2.53)	(0.44)
COOP		-0.02		0.04		-1.05		-0.07		-0.35		1.27
		(-0.05)		(0.10)		(-0.59)		(-0.22)		(-1.01)		(1.35)
SUPPORT		0.97***		1.14***		-0.59		1.18***		1.24***		0.82
		(3.81)		(4.42)		(-0.56)		(5.27)		(5.21)		(1.34)
INFO_IN		0.12		0.26		-1.11		0.31		0.16		0.64
		(0.41)		(0.89)		(-0.93)		(1.32)		(0.65)		(1.01)
INFO_EX		0.18		-0.03		2.29**		0.13		0.09		0.33
		(0.68)		(-0.13)		(2.10)		(0.58)		(0.40)		(0.55)
EXP	0.16***		0.16***		0.17		0.36***		0.35***		0.44***	
	(4.00)		(3.60)		(1.58)		(10.08)		(8.77)		(5.07)	
LSIZE	0.24***		0.24***		0.18***		0.16***		0.17***		0.11***	
	(12.52)		(11.85)		(3.02)		(8.88)		(8.64)		(2.58)	
_cons	-1.68***	-2.47**	-1.70***	-2.19*	-1.39***	-6.58	-1.46***	-4.91***	-1.48***	-3.40***	-1.43***	-10.67***
	(-18.52)	(-2.02)	(-17.56)	(-1.77)	(-5.02)	(-1.11)	(-18.02)	(-4.41)	(-16.74)	(-3.02)	(-6.80)	(-2.99)
Lambda	5.34***		5.21***		7.14*		6.42***		5.42***		9.58***	
	(6.42)		(6.15)		(1.77)		(8.53)		(7.02)		(4.31)	
Rho	0.74		0.75		0.78		0.85		0.79		0.98	
N	7,185	2,080	6,236	1,880	949	200	7,329	2,458	5,988	2,054	1,341	937

t- statistics in brackets: * Significant at 10%; **5%;***1%. All regressions include industry dummies (results available upon request).

Table 5. Knwoledge Production Function: Product and Process Innovation (CIS3 - CIS 4)

	CIS3						CIS4					
	TOT		MATURE		YOUNG		TOT		MATURE		YOUNG	
Dep. Var.	PROD	PROC	PROD	PROC	PROD	PROC	PROD	PROC	PROD	PROC	PROD	PROC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{RDT}$	0.81***	0.33***	0.83***	0.35***	0.54***	0.30***	0.41***	0.02	0.42***	0.05	0.46***	0.20**
	(9.11)	(5.93)	(8.41)	(6.80)	(3.55)	(3.03)	(7.82)	(0.40)	(7.57)	(1.14)	(3.77)	(2.02)
$\widehat{TAT}$	0.79***	0.84***	0.73***	0.77***	0.32**	0.37***	0.98***	1.27***	0.86***	1.09***	0.42**	0.56***
	(9.09)	(11.33)	(9.22)	(11.22)	(2.28)	(3.11)	(11.52)	(14.61)	(9.81)	(15.46)	(2.43)	(4.16)
IORG	0.37***	0.45***	0.38***	0.44***	0.34**	0.52***	0.34***	0.47***	0.34***	0.47***	0.41***	0.56***
	(8.79)	(11.35)	(8.94)	(10.23)	(2.25)	(4.11)	(8.52)	(14.60)	(7.12)	(11.14)	(3.24)	(5.59)
IMARK	0.63***	0.25***	0.62***	0.24***	0.83***	0.37***	0.61***	0.34***	0.60***	0.33***	0.74***	0.47***
	(13.85)	(6.81)	(12.88)	(5.28)	(6.28)	(3.03)	(14.68)	(8.14)	(10.28)	(7.44)	(5.29)	(3.97)
LSIZE	0.18***	0.17***	0.17***	0.16***	0.22***	0.16**	0.27***	0.27***	0.24***	0.22***	0.27***	0.26***
	(9.06)	(8.44)	(7.73)	(8.81)	(2.70)	(2.28)	(14.07)	(15.93)	(10.24)	(12.77)	(4.79)	(5.97)
_cons	-3.00***	-2.60***	-2.91***	-2.53***	-2.55***	-1.89***	-3.57***	-3.01***	-3.40***	-2.76***	-3.07***	-2.44***
	(-19.93)	(-17.90)	(-21.25)	(-19.91)	(-8.55)	(-6.29)	(-23.39)	(-29.44)	(-20.63)	(-24.46)	(-9.20)	(-10.11)
Rho	0.62		0.61		0.74		0.46		0.47		0.54	
N	7,185		6,236		949		7,329		5,988		1,341	

t- statistics in brackets: * Significant at 10%; **5%;***1%. All regressions include industries dummies (results available upon request).

Appendix

Table A1. The variables: acronyms and definition

Innovative input variables	
RDT_d	Dummy = 1 if firm's R&D expenditures (both intramural and extramural) are positive
RDT	Total firm's R&D expenditures (both intramural and extramural), normalized by total turnover
TAT_d	Dummy = 1 if firm's expenditures for Technological acquisitions (investment in new machinery and equipment and purchasing of external technology incorporated in licences, consultancies and know-how) are positive
TAT	Total firm's expenditures for technological acquisitions, normalized by total turnover
Innovative output variables	
PROD	Dummy = 1 if the firm has introduced new or significantly improved products
PROC	Dummy = 1 if the firm has introduced new or significantly improved processes
Firm's general characteristics	
IG	Dummy = 1 if the firm belongs to an industrial group
Innovative-relevant information	
PATDEP	Dummy = 1 if the firm have applied for patents
PROT	Dummy = 1 if the firm adopts other instruments of protection of innovation activities than patents (trademarks, copyright, registration of design)
COOP	Dummy = 1 if the firm takes part into cooperative innovative activities
SUPPORT	Dummy = 1 if the firm has received public support for innovation
INFO_IN	Dummy = 1 if the firm has used any type of internal source of information for its innovation activities
INFO_EX	Dummy = 1 if the firm has used any type of external source of information for its innovation activities
EXP	Dummy =1 if the firm have traded in an international market during the three year period; 0 otherwise
LSIZE	Log of the total number of firms' employees
IORG	Dummy = 1 if the firm has realized managerial, strategic or organizational innovation
IMARK	Dummy = 1 if the firm has implemented changes in marketing concepts or strategies (e.g. packaging or presentational changes to a product to target new markets)