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Intangible resources: the relevance of training for European firms' innovative performance

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Abstract This study investigates the effect that spending in on-the-job training directly aimed at developing and/or introducing innovation and skilled human capital has on innovative sales. In particular, it investigates whether or not the returns on these investments differ between small and medium-sized enterprises (SMEs) and large firms, and the extent to which returns are affected by a firm's knowledge intensity. Using data from the third Community Innovation Survey, covering 23 European countries, this paper estimates a system of three equations in which investments in training and in the stock of R&D personnel are treated as endogenous in relation to the amount of innovative sales on which they are presumed to have an effect. Empirical evidence confirms that investments in training and in the stock of R&D personnel have a positive effect on firms' innovativeness and that returns on them are not affected by the degree of knowledge intensity of the firm. However, the returns are always statistically significantly higher in large firms than in SMEs.

Keywords Intangibles · R&D investment · Human capital · Training · CIS · CDM model

JEL Classification O30 · O31 · O32 · D83 · D62

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1 Introduction

This study investigates the effect that spending in on-the-job training directly aimed at developing and/or introducing innovation and skilled human capital has on innovative firms' performance. More specifically, it aims to ascertain whether or not the returns on these investments in terms of sales of products new to the market (innovative sales) differ between small and medium-sized enterprises (SMEs) and large firms, and whether or not returns are affected by a firm's knowledge intensity.[1]

The general idea behind is that the knowledge created by a workforce trained to develop and/or introduce innovations can be better socialised and circulated within the firm (Boothby et al. 2010). This means that the effectiveness of innovation is contingent upon investment in the necessary human capital and training to support new technologies (Piva and Vivarelli 2009).[2] Stated simply, the better the people who manage a firm's knowledge are trained in developing or introducing innovation, the better a firm's performance (O'Dell and Jackson 1998). *Specific-to-the-firm* training contributes both to fostering knowledge circulation and to the production of new knowledge. Better knowledge circulation increases the sharing of tacit knowledge between individuals (Nonaka et al. 2000) and the absorptive capacity (Cohen and Levinthal 1989, 1990) of the firm, and consequently its ability to convert ideas into new products and sell them.

However, it is reasonable to presume that the same amount of expenditure on training may generate different returns (in terms of innovation output) according to the size of the firm carrying it out and its stock of skilled workers. For instance, returns on training might differ between smaller and larger firms because of the different types of training provided and depending on the stock of available human capital on which to build.[3] Larger firms provide more frequent, formal and institutionalized training that guarantee continuous lifelong learning than smaller firms, which face greater financial constraints. In addition, smaller firms may find it more difficult to quickly adapt workers' skills to the permanent evolution of job requirements resulting from the high speed at which technological change occur, which requires the continuous upgrading of a firm's labour force.

Similarly, returns on research and development (R&D) personnel, which in the following is used as a proxy for a firm's stock of human capital and its innovation effort, may be affected by the scale of production because the larger the firm, the larger the amount of other intangible resources, for example personnel in marketing, design, etc., that can be combined to favour the success of a product and to make the most of knowledge circulation. Although smaller firms are more flexible, they often tend to have limited resources and competences, and, as a consequence, R&D returns tend to be greater in larger firms (Lichtenberg and Siegel 1991).

[1] To this end, I borrowed the Eurostat concept of knowledge-intensive activities (KIA) (Eurostat NACE Rev. 2 definition), which are identified by considering the educational attainment of the workforce, and I defined all firms in which over 33% of the workforce is educated to tertiary level as knowledge intensive.

[2] If skills are in short supply, a firm may decide not to invest in technologies for which a high level of human capital is necessary.

[3] I need to thank an anonymous referee for their suggestion to clarify this point.

The argument behind the hypothesis of differences in returns on training and R&D personnel due to differences in knowledge intensity between firms hinges on the abovementioned idea that the larger the stock of skilled employees, the larger will be the stock of knowledge on which the new knowledge created through training can build. Therefore, assuming the existence of knowledge spillovers at firm level and among employees, we might argue that the return on an investment in training and/or R&D personnel would be expected to be larger the larger was the stock of in-house skilled human capital. In addition, training and R&D are a prerequisite for benefiting from these spillovers. To the extent that larger firms invest more (and on a more continuous basis) in training and skilled human capital than smaller firms and that these expenditures increase productivity at firm level, it follows that larger firms may gain a competitive advantage.

To examine these issues, this study uses non-anonymous data from the third wave of the European Community Innovation Survey (CIS),[4] which concern 1998–2000 and cover 23 European countries (Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden). The choice to use this wave of the survey rather than one of the more recent ones was made because this was the last wave to collect firm-level information on the number of employees with tertiary education, and it provides more detailed information on training expenditures. These two features allowed, unlike in the majority of CIS-based studies, the use of continuous variables as the main variables of interest (R&D personnel and investments in training), with dummy variables used only as controls.

The paper is structured as follows: Sect. 2 briefly outlines the theoretical framework; Sect. 3 uses this theoretical framework to present an empirical model for estimating the impact of work-based training and R&D employees on innovativeness, as well as describing the dataset used; Sect. 4 discusses the empirical results; and Sect. 5 concludes.

2 Theoretical background

Even though it was Mincer (1989) who pointed out the dual role of human capital in the process of economic growth (as a stock of skills it is a factor of production, and as a stock of knowledge it is a source of innovation), the traditional Beckerian framework (Becker 1964) remains the principal theoretical economic construct used to understand the process of skill formation and development within firms. In Becker's view, what makes a firm willing to train its workforce is the possibility of enhancing its specific skills (rather than 'general' skills), which are not easily replicable. As the provision of more specific training decreases the possibility that workers can 'sell' it to other firms, it creates an *ex ante* incentive for workers to underinvest in it (Layard et al. 1995; Hansson 2009). In fact, specific skills have no (or limited) value outside of the current place of employment. In the case of

[4] The research was carried out at Eurostat's Safe Centre in Luxembourg.

'transferable' skills (Stevens 1996), however, which are neither completely specific nor completely general, positive externalities for other firms are the general rule: because of staff turnover, the investment made by one employer in an employee's training has the potential to generate profit for another. Clearly, these externalities creates an incentive for poaching, which increases turnover and reduces the incentive to train (Stevens 1996; Katz and Ziderman 1990; Hansson 2009).

As far as the roles of human capital and training are concerned, in more managerial-oriented approaches, such as the knowledge-base view (KBV) (Spender 1989; Grant 1996) and human resource management (HRM) (Baird and Meshoulam 1988; Jackson and Schuler 1995; Huselid et al. 1997; Leiponen 2005), skills are an important component of absorptive capacity. Within these frameworks, knowledge acquisition is not simply about recruiting outstanding people; it is also about helping them to learn and grow as individuals and professionals, by creating a supportive environment and investing in training and development (Senge 1994). Skills are considered complementary to internal R&D and external collaboration strategies, and they can have a positive effect on firms' profit margins (Leiponen 2005). Because of the complexity inherent in human resource management practices and specific on-the-job training, competitors can neither easily copy these practices nor readily replicate the unique pool of human capital that such practices help create (Huselid et al. 1997).

The empirical literature on the impact of human capital on a firm's innovative performance generally shows that when a firm has the possibility of generating a human capital[5] advantage and attracting a stock of human talent, it is more innovative than the average firm (Lundvall and Nielsen 2007; Svetlic and Stavrou-Costea 2007). Skilled people can deal with complexity, and job complexity has a positive relationship with innovation, suggestion-making and creativity (Song et al. 2003; Piva and Vivarelli 2009). Although firm-level data regarding the amount and/or nature of training provided are scarce, there is increasing evidence that training generates substantial benefits for employers (Hansson 2009), although there is mixed evidence regarding the various kinds of training (Tamkin 2004). The most compelling evidence is found in several empirical papers that link training investment with changes in firms' productivity, profitability and stock market performances (d'Arcimoles 1997; Barrett and O'Connell 1999; Groot 1999; Dearden et al. 2000; Hansson 2009; Boothby et al. 2010). Boothby et al. (2010) found that firms adopting advanced technologies and at the same time providing strategic training were, on average, more productive than other technology adopters which, in turn, were more productive that firms that did not use advanced technologies at all. Ballot et al. (2001) used firm-sponsored training—measured by the percentage of the total wage bill devoted to continuous training and by the hours of training paid for by the firm—to examine the effect of human capital on performance in a sample of 90 large French firms and 272 large Swedish firms during the period 1987–1993. Results show that, like R&D capital, human capital

[5] In the empirical literature on the impact of human capital on firms' performance, the most common proxies used for this category of intangibles are labour costs (Lin 2007), the level of education of the workforce (Crepon et al. 1998; Loof and Heshmati 2002; Aiello and Pupo 2004), the number of researchers and the level of training.

also has a significant and positive effect on performance. The empirical literature on human capital has also used both training-related and education-related data. For instance, Lybaert et al. (2006) used the proportion of highly educated personnel and the percentage of personnel involved in training programmes to measure the effect of knowledge capital on a sample of 259 Belgian firms. However, the results of such studies depend heavily on the performance measure used. In addition, only education level appears to have a positive effect on performance, whereas conclusive results cannot be reached for training level. Whitfield (2000), using a dataset based on a nationally representative sample of British establishments, suggested that firms exhibiting high-performance work practices have higher levels of training and those with a comprehensive set (or bundle) of these practices exhibit much higher levels than those that do not. Overall, however, empirical results are not always conclusive, as there are also a number of studies that do not support the idea that training and human capital have a positive effect on a firm's performance (e.g. Lybaert et al. 2006).

3 Methodological approach and data

3.1 Methodology

A firm can decide what types of skills and competences it aims to create and/or reinforce in its labour force through firm-specific training programmes, unlikely to be replicable by would-be competitors. That is why, whereas proxies of human capital (such as education level) relate more to the individual, the amount of training provided relates more to the firm. Therefore, the amount of expenditure on external and internal training directly aimed at the introduction of innovations is used, in the following, as a proxy for the flow of new firm-specific knowledge. In addition, the number of people employed in R&D activities is used to proxy the stock of R&D-relevant human capital on which the new knowledge can build.

Modifying the modelling approach of Crepon et al. (1998), I estimated three equations with a two-step procedure in which the inputs to the innovation process (training expenditure and the number of people employed in R&D) are related to their output (innovative sales) and all are treated as endogenous variables.[6]

The first step consists in estimating two relations. The first equation explains the firm's decision on whether or not to engage in training (either in house or external) directly aimed at developing and/or introducing innovations, and on how much resource to invest in it (*TR*). The second equation explains the firm's stock of workers directly involved in R&D activities (*RDpers*). The second step consists in estimating a third relation (*INNO*), which explains the amount of a firm's innovative sales as a function of the investments in training and in R&D personnel (which is also a proxy for a firm's involvement in R&D activities) and of other characteristics of the firm. The relations are as follows:

[6] In Crepon et al. (1998) there was a third block, namely the link between innovation inputs and firms' productivity.

First step:

$$TR = TR* \text{ if } TR* = \beta_{TR} z_1 + \beta_{TR} z_c + \varepsilon_{TR} \geq 0$$
$$0 \text{ if } TR* = \beta_{TR} z_1 + \beta_{TR} z_c + \varepsilon_{TR} < 0$$

$$RDpers = RDpers* \text{ if } RDpers* = \beta_{RDpers} z_2 + \beta_{RDpers} z_c + \varepsilon_{RDpers} \geq 0$$
$$0 \text{ if } RDpers* = \beta_{RDpers} z_2 + \beta_{RDpers} z_c + \varepsilon_{RDpers} < 0$$

Second step:

$$INNO = INNO* \text{ if } INNO* = \beta_{inno} TR* + \beta_{inno} RDpers* + \beta_{inno} z_3 + \beta_{inno} z_c + \varepsilon_{inno} \geq 0$$
$$0 \text{ if } INNO* = \beta_{inno} TR* + \beta_{inno} RDpers* + \beta_{inno} z_3 + \beta_{inno} z_c + \varepsilon_{inno} < 0$$

where *TR** is a latent training variable and *RDpers** is a latent R&D personnel variable, z_1, z_2 and z_3 are vectors of explanatory variables specific to each equation, and z_c is a vector of common controls. ε_{TR}, ε_{HK} and ε_{INNO} are normally distributed error terms with zero mean and standard deviations of σ_t^2, σ_h^2 and σ_i^2 respectively.

The use of the two latent variables (*TR** and *RDpers**) is justified both on methodological grounds—it is the only way in which a system can be defined using non-linear estimations—and on theoretical grounds. The use of latent variables for training and R&D personnel (and not of their observed values) implies that all innovative firms are considered, as the sample is not restricted to training-providing firms or firms with R&D workers. In fact, the inclusion in the regression of the predicted training effort and of predicted R&D personnel accounts for the fact that all firms may make some kind of innovative effort, even though only some of them invest in training and/or have R&D employees. Besides, using the predicted values instead of the observed ones is also a wise way to "instrument the innovative effort in the knowledge production function to deal with the simultaneity issue between R&D/training effort and the expectation of innovative success" (Hall et al. 2009). Finally, as investments in training and in the stock of R&D employees not only affect a firm's performance but also are likely to produce positive externalities (and thus also affect a firm's competitors by increasing the pool of knowledge available to other firms (Romer 1994; Aghion et al. 1998), using predicted values (instead of realised values) can also be considered a way to capture these positive externalities.

However, one caveat and a couple of drawbacks of the empirical model have to be mentioned. First, the CIS questionnaire distinguishes between two categories of innovative product: new to the market ('TurnMar' in the CIS questionnaire) and new to the firm ('TurnIn' in the CIS questionnaire). This paper adopts the former category, which is generally considered to better proxy truly creative behaviour, as the latter tends to reflect the results of firms' imitative behavior. Second, the estimated coefficients identify a set of correlations rather than causal relations. Although using the predicted value of R&D workers and *TR* could reduce the simultaneity bias and help in dealing with endogeneity, it is also true that such predicted values are explained by variables measured over the same period (1998–2000). In addition, identifying a causal effect of training and R&D on innovation output may be difficult in the presence of a lagged adjustment process that, given the cross-sectional nature of the database used, cannot be modelled. Therefore, the objective of the following analysis is not to test cause–effect relationships, but to assess the significance and intensity of the correlation relationships between the main variables of interest. In addition, the restriction of the sample to innovative firms only (there is no information on non-innovative firms) may lead to bias in the estimates of returns on training and R&D employees.

3.2 Data: innovation inputs and outputs

The CIS is conducted in every EU Member State to collect data on firms' innovation activities. Enterprises are asked about the kind of innovation introduced (product and/or process) and the specific innovation activities carried out over the three year period covered by the survey, if any. Innovative firms[7] (firms that have introduced process or product innovations in the three year period covered by the survey or had recent innovation activity) are then asked to give information about their share of sales due to new or significantly improved product, about expenditures and human resources dedicated to R&I activities, along with more qualitative information, such as the sources of information used during the innovation process, the objectives pursued and effects obtained, the hampering factors associated to it, etc.

In the empirical analysis, I have used the third wave of the CIS (1998–2000), made available by Eurostat at its Safe Centre in Luxembourg. The data are based on a representative sample of manufacturing and service firms with more than 9 employees, covering 23 Member States (Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden). The third wave of the CIS was the last in which Member States had to provide to Eurostat information both on the amount spent on R&D and on the total amount spent on training, marketing and design; this information was provided for the reference year 2000. Information is available only for innovative firms.

In the CIS questionnaire, innovation activities are classified in five main categories (intramural R&D, extramural R&D, acquisition of machinery and equipment, acquisition of external knowledge and training/marketing/design). Expenditures on training, marketing and design represented 6% of the overall expenditure on innovation activities of the innovative firms in the sample (Fig. 1).

Among those firms that engaged in technological innovation between 1998 and 2000 [32,583 enterprises out of 87,340 were innovators[8] (Table 1)], 13,527 firms stated that they had engaged in training-related innovation activities in 2000. They represented 41.5% of the innovative firms in the sample and almost 54% of the product innovators. Almost 83% of firms investing in training were SMEs (as

[7] Innovative firms represented 37% of the overall CIS sample of European firms, that is, 32,583 enterprises out of 87,340.

[8] Firms that reported zero turnover or zero employees were removed from the original dataset. Among innovative firms, successful product innovators during the period 1998–2000 represented 77%.

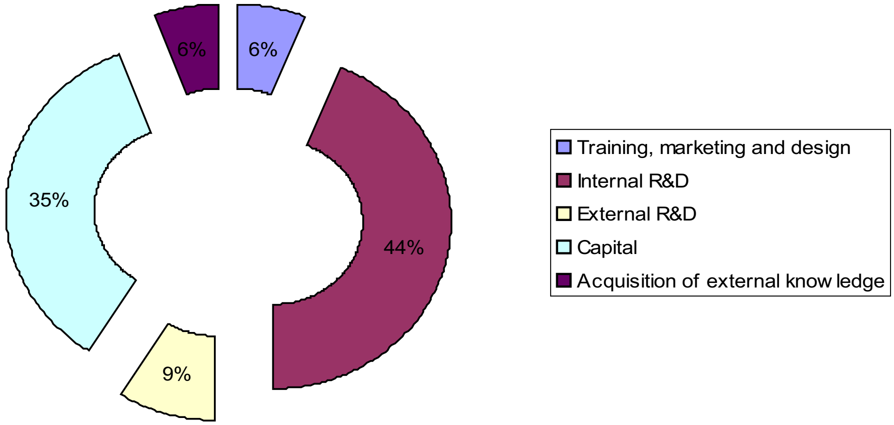

Fig. 1 Innovation activity expenditure structure, CIS3. Source: Authors' elaboration on CIS3 data

Table 1 The CIS3 sample

	Number of firms	% with respect to all firms (innovative and not innovative)	% with respect to innovative firms
Innovative and non-innovative firms in the CIS3 sample	87,340	100	–
Innovative firms	32,583	37	100
Product innovators	25,042	28.7	77
With positive internal R&D	14,976	17.1	46

Source: Authors' elaboration on CIS3 data

defined by the European Commission in its Recommendation No 2003/361/EC, a firm is an SME if the number of employees is <250 and the amount of sales is ≤€50,000,000). The number of firms engaged in innovation-related activities and the proportions that they made up of the whole sample and of the sample of product innovators is presented in Table 1.

To correctly identify the amount of training directly aimed at the development and/or introduction of innovations,[9] the analysis considers only those firms that stated in the questionnaire that they had invested in training and not in marketing and design. In these cases, the amount reported in the survey coincides with the firm's expenditure on training.[10] This choice allowed the calculation of the amount

[9] It is not possible to know the extent to which this training is aimed at R&D workers and to which it is aimed at other workers, such as administrative staff who need to learn to use new accounting software for a new product line.

[10] Among the firms that declared a positive expenditure on training activities, 5134 had engaged in training, marketing and design activities and 4125 stated that they had engaged in training activities only. In addition, 2701 had engaged in training and marketing activities but not in design activities, whereas 1487 had engaged in training and design activities but not in marketing activities.

Table 2 Distribution of innovators with training, marketing and design activities

	Number of firms
Firms with expenditures on training	13,527
Firms with expenditures on marketing	10,779
Firms with expenditures on design	9204

Source: Authors' elaboration on CIS3 data

invested in internal and/or external training by a firm—it is how much a firm invests in training that makes the difference (Hansson 2009)—and, consequently, the isolation of the direct effects of expenditure on training on innovative sales. However, this option led to the underestimation of the number of firms that actually invest in training and of the importance of complementarity among intangible expenditures (i.e. training, marketing, and design), as those that invested in marketing activities directly aimed at the introduction into the market of new or significantly improved products *as well as* in design were not considered (see Table 2).[11] However, this was the only way to isolate training expenditures and their contribution. The log of (expenditure on training directly aimed at the development and/or introduction of innovations + 1) was then used as a dependent variable. Standard checks for outliers were performed and only few abnormal values for training expenditures were identified (and removed from the observations).

As far as the other two dependent variables are concerned, *RDpers* is the natural logarithm of (number of workers who were involved in intramural R&D activities in 2000[12] + 1); *INNO* is the natural logarithm of (amount of firm's innovative sales in 2000 + 1) and measures product innovation. The amount of a firm's innovative sales was calculated by multiplying the proportion of innovative sales (new or significantly improved products/services) introduced during the period 1998–2000 by the firm's total turnover for 2000. The choice of using product innovation instead of process innovation as the output of the innovation process, although the relation between the latter on the one hand and training and R&D personnel on the other is probably stronger, was made owing to the preference for the use of continuous variables rather than dichotomous ones.

3.3 The econometric model

The three aforementioned relationships were estimated using a generalised Tobit model, as is commonly done in the literature (e.g. Crepon et al. 1998). In fact,

[11] There is another source of measurement bias, which probably implies an underevaluation of the firms' total investment in training (and not of the number of firms investing, as in the previously discussed case), as spending on firm, specific human capital consists of two types of expenses (Corrado et al. 2005): the amount and the *time* spent on training. Given the information available and the data used, I was able to consider only the former.

[12] As a robustness check, the system of equations was also estimated using R&D total investment (intramural and extramural R&D) instead of the amount of R&D personnel as a proxy for innovative input. The significance and signs of the variables of interest did not vary.

although the sample was restricted to innovative firms, a large proportion of these reported zero expenditure on training and/or R&D employees or zero innovative sales. Theoretically, however, this standard model should be used if the underlying dependent variable contains negative values that have been censored to zero in its empirical realisation (Sigelman and Zeng 1999). If that is not the case, the de facto alternative would be the Heckit model (which includes the Tobit model as a specific case). The Heckit model should be preferred when values cluster at zero as a consequence of sample selection and not censoring. In the case analysed in this paper, however, the zero values of the dependent variables are not a result of selection bias, as the sample is restricted to innovators (e.g. a zero value for innovative sales is not due to the presence of non-innovators in the sample). Furthermore, the Heckit model is 'inappropriately seized upon as an alternative to Tobit for analysing exclusively nonnegative data', such as those in the current case, and its use would result in information loss and inefficient estimates (Sigelman and Zeng 1999). In practice, the Tobit model is employed when the values of the observed dependent variable are exclusively non-negative and are clustered to zero, irrespective of the fact that any censoring has occurred (Sigelman and Zeng 1999).[13]

The explanatory variables included in the system of equations are explained below. For the sake of simplicity, I describe first the variables that are common to the entire set of equations (z_c), and then the set of variables specific to each equation (z_1, z_2 and z_3). A crucial assumption to ensure parameter identification is the existence of exclusion restrictions, that is, variables affecting the innovation outcome but not the amount spent on training or the stock of human capital. The choice of these restrictions is based on theoretical grounds, but it is also based on the significance of the estimated coefficients, as non-significant coefficients might be poor instruments with which to identify the model's key parameters.[14] Therefore, my exclusion restrictions are two dummies capturing the introduction of advanced management techniques and of changes in the aesthetic appearance of products, both introduced in the *INNO* equation. The idea is that these capture sort of propensities to invest in 'intangibles' that might be more relevant to be able to successfully introduce new products into the market than to determine the amount spent on training and the stock of human capital. Table 3 reports the description of the dependent and explanatory variables included and details the usual descriptive statistics.

To check for robustness, five slightly different systems of equations were estimated but only those for the reference model are reported and commented on (Table 4).[15] Finally, since in the last stage of the model I use predicted values, there is a need to correct for standard errors and account for this feature in the model. Therefore, the innovative sales equation was estimated with bootstrap resampling

[13] In this regard, it is true that the appropriate procedure would be to model the decision that has produced the zero observations, rather than using the Tobit model mechanically. However, the nature of the dependent variables and the database used in this analysis did not allow this modelling option.

[14] Preliminary checks for multicollinearity were performed and a high value of correlation was found for R&D investments and R&D personnel, hence the exclusion of R&D investments from the determinants of the innovation output equation.

[15] The results of the robustness checks are available upon request.

Table 3 Descriptive statistics

	Description	Obs.	Mean	SE	Min.	Max.
Dependent variables						
TR	Amount of investment in training direct at the introduction of new products (log)	42,349	0.420113	1.57574	0	15.992
RDpers	Number of R&D personnel (log)	58,357	0.5634781	1.120578	0	9.577
INNO	Amount of innovative sales, i.e. new to the market products (log)	62,933	5.455105	7.035876	0	24.69
Independent variables						
Advanced management strategies (Actman)	Dummy variable taking up the value 1 if the firm implemented advanced management techniques during the period 1998–2000, 0 otherwise	85,882	0.2445565	0.4298264	0	1
New organisational structures (Actorg)	Dummy variable taking up the value 1 if the firm implemented new or significantly changed organisational structures during the period 1998–2000, 0 otherwise	85,880	0.3150442	0.4645362	0	1
New marketing concepts/strategies (Actmar)	Dummy variable taking up the value 1 if the firm significantly changed its marketing concepts/strategies during the period 1998–2000, 0 otherwise	85,883	0.2246195	0.417334	0	1
New design, aesthetic changes (Actaes)	Dummy variable taking up the value 1 if the firm significantly changed its product's appearance/design during the period 1998–2000, 0 otherwise	85,863	0.2448435	0.4299969	0	1
Lack of finance (Hfinzeroone)	Dummy variable taking up the value 1 if the firm declared a lack of appropriate sources of financing as a hampering factor, 0 otherwise	70,302	0.4793889	0.4995786	0	1
Lack of qualified personnel (Hperzeroone)	Dummy variable taking up the value 1 if the firm declared a lack of qualified personnel as a hampering factor, 0 otherwise	70,220	0.4313016	0.4952616	0	1
Organisational rigidities (Horgzeroone)	Dummy variable taking up the value 1 if the firm declared organisational rigidities as a hampering factor, 0 otherwise	70,157	0.3656371	0.4816118	0	1
Funding	Dummy variable taking up the value 1 if the firm received public financial support for innovation activities, 0 otherwise	33,821	0.2846161	0.4512381	0	1
Patent activity (Paap)	Dummy variable taking up the value 1 if the firm applied for at least one patent over the period 1998–2000, 0 otherwise	85,726	0.083032	0.2759322	0	1

Table 3 continued

	Description	Obs.	Mean	SE	Min.	Max.
Existence of valid patents (Paval)	Dummy variable taking up the value 1 if the firm had valid patents at the end of 2000, 0 otherwise	85,724	0.078231	0.256432	0	1
Cooperating firm (co)	Dummy variable taking up the value 1 if the firm cooperated on innovation activities with other enterprises and/or institutions during the period 1998–2000, 0 otherwise	34,409	0.2902148	0.453868	0	1
R&Dconstant (rdconst)	Dummy variable taking up the value 1 if the firm constantly invests in R&D, 0 otherwise	20,062	0.5834912	0.4929922	0	1
Univerities as source of information (sunizeroone)	Dummy variable taking up the value 1 if the firm declared universities as the main source of information needed for suggesting new innovation projects during the period 1998–2000, 0 otherwise	33,802	0.3513993	0.4774145	0	1
Clients as source of information (sclizeroone)	Dummy variable taking up the value 1 if the firm declared clients as the main source of information needed for suggesting new innovation projects during the period 1998–2000, 0 otherwise	33,808	0.7198888	0.44906	0	1
Group	Dummy variable taking up the value 1 if the firm belongs to a group, 0 otherwise	86,839	0.3004526	0.4584575	0	1
dummyKIA	Dummy variable taking up the value 1 if the firm has a workforce more than 33% of which has tertiary education, 0 otherwise	87,499	0.2675345	0.442676	0	1
sme	Dummy variable taking up the value 1 if the firm has a number of employees <250 and an amount of sales $\leq 50{,}000{,}000$, 0 otherwise	79,845	0.9228881	0.2667706	0	1
Employees (lnemp)	Number of employees (log)	87,344	3.958507	1.320868	0.6931472	12.68913
Industry dummies (2-digit level)						
Manufacture						
High-tech	NACE 30 + 32 + 33	87,499	0.0305489	0.1720931	0	1
Medium-high-tech	NACE 24 + 29 + 31 + 34 + 35	87,499	0.1325158	0.3390526	0	1
Medium-low-tech	NACE 23 + 25 + 26 + 27 + 28	87,499	0.1399902	0.3469788	0	1
Low-tech	NACE 15 + 16 + 17 + 18 + 19 + 20 + 21 + 22 + 36 + 37	87,499	0.3235008	0.4678147	0	1
Electricity	NACE 40 + 41	87,499	0.0202745	0.1409386	0	1
Services						

Table 3 continued

	Description	Obs.	Mean	SE	Min.	Max.
Market service low	NACE 51 + 60 + 63	87,499	0.2095338	0.4069782	0	1
Financial services	NACE 65 + 66 + 67	87,499	0.0370519	0.18889	0	1
High tech services	NACE 64 + 72 + 73	87,499	0.0424919	0.2017097	0	1
Low-tech services	NACE 50 + 60 + 63	87 499	0.0499663	0.2178766	0	1
Country dummies (NUTS 2 level)	Austria, Belgium, Bulgaria, the Czech Republic, Estonia, Finland, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Norway, Portugal, Romania, Slovakia, Slovenia, Spain					

Table 4 Tobit estimation results (average marginal effects), new-to-the-market products

Variables	(a) Training	(b) R&D personnel	(c) Innovative sales
latent_TR			0.277*** (0.0732)
latent_RDpers			3.908*** (0.210)
Funding		0.321*** (0.0177)	
Constant R&D		0.792*** (0.0156)	
New organisational structures	1.325*** (0.156)	0.0106 (0.0171)	
Advanced management strategies	3.042*** (0.181)		
Lack of qualified personnel	1.795*** (0.146)		
Clients as source of information			2.718*** (0.237)
Universities as source of information	1.084*** (0.153)		
New design (aesthetic changes)			0.922*** (0.123)
New marketing concepts/strategies			2.692*** (0.197)
Existence of valid patents			0.583*** (0.0943)
Cooperating firm		0.192*** (0.0147)	
% tertiary educated workers	0.119** (0.0456)		
Lnemp	0.476*** (0.0542)	0.521*** (0.00623)	1.808*** (0.218)
Gp	0.814*** (0.158)	−0.00786 (0.0174)	−1.453 (0.128)
High-tech	2.171*** (0.901)	0.832*** (0.0843)	0.303 (0.219)
Medium–high-tech	2.5726*** (0.746)	0.527*** (0.0911)	1.913 (1.183)
Medium–low-tech	1.753** (0.753)	0.0501 (0.0861)	1.557 (1.136)
Electricity	2.421*** (0.785)	−0.157 (0.146)	2.369** (1.133)
Financial services	4.575*** (0.774)	0.281*** (0.0874)	−3.554** (1.409)
High-tech services	4.872*** (0.805)	0.576*** (0.0893)	2.199* (1.159)
Low-tech services	1.673*** (0.726)	1.074*** (0.071)	0.634 (1.247)
Wald Chi2[a]	572,125	682,141	886,959
AIC	32,431.21	44,265.45	101,287
BIC	31,652.14	44,366.91	101,465.6
Observations	31,616	17,767	17,495

Bootstrapped standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other controls: 22 country dummies. High-tech, NACE 30 + 32 + 33; Medium-high-tech, NACE 24 + 29 + 31 + 34 + 35; Medium-low-tech, NACE 23 + 25 + 26 + 27 + 28; Low-tech, NACE 15 + 16 + 17 + 18 + 19 + 20 + 21 + 22 + 36 + 37; Electricity, NACE 40 + 41; Financial services, NACE 65 + 66 + 67; High-tech services, NACE 64 + 72 + 73; Low-tech services, NACE 50 + 51 + 60 + 63. Other controls: 22 country dummies

[a] With 35 degrees of freedom (df), 37 df and 41 df, from left to right

procedures (Efron 1982) using 50 replications, which takes account of both selectivity and endogeneity.

3.3.1 The common set of independent variables

The common set of independent variables (z_c) includes those that identify a firm's structural characteristics (Antonelli et al. 2010): firm size (*lnempl*), firm location (23 country controls; reference group: Germany), firm industry specialisation (9 industry controls for low-tech, medium-low-tech, medium-high-tech and high-tech manufacturing and service sectors, following the Eurostat classifications (see Table 4 for a description); reference group: low-tech manufacturing sector) and a dummy controlling for firms belonging to a group (*group*).

The control for firm size was introduced because it is generally recognised that large firms tend to exploit economies of scale and scope better, and this cost advantage translates into a competitive advantage. Using a sample of Italian manufacturing firms, Antonelli et al. (2010) demonstrated that larger firms tend to train a higher proportion of their workforce than SMEs, but that medium-sized firms tend to spend more on average than their small and large competitors. Black et al. (1999) argue that large firms have scale economies in the provision of both formal and informal training, and more opportunities for so-called co-worker training: if there is more than one employee carrying out a specific task, then one of them can temporarily suspend his/her job to teach a new worker without interrupting the productive process. Similarly, Baldwin et al. (1995) claimed that large firms invest more because they tend to have greater returns on their investments, whereas Holtmann and Idson (1991) argue that larger firms face lower investment risks because they 'pool risks'. In addition, according to Hashimoto (1979), large firms have access to cheaper capital to finance training. As far as sectoral controls are concerned, it is often argued that some industries have higher or lower average expenditure on R&D 'by nature', and that a firm's new product sales are decisively influenced by the typical length of the lifecycle of the product in question (Paananen and Kleinknecht 2010). Firms selling products that experience shorter lifecycles will introduce new products relatively more frequently and will have a higher proportion of total sales of such products than firms whose products are characterised by longer lifecycles. Furthermore, sectoral controls may help to identify the technology constraints imposed on the conversion of skills acquired into skills used (Guidetti and Mazzanti 2007). In addition, the efficacy of different mechanisms for ensuring a firm's appropriation of the value generated is likely to vary across industries (Villalonga 2004) and countries. Similarly, innovative activity has a high propensity for spatial clustering in high-tech industries (pharmaceuticals, electronic components, semiconductors, photographic equipment, surgical and medical instruments, etc.), sectors where new economic knowledge predominates (Audretsch and Feldman 1996). Finally, the control for the impact of foreign subsidiaries was introduced to account for the fact that such firms' innovative output may be consistently higher, as they can take advantage of knowledge transfers from the parent company (Antonelli et al. 2010).

3.3.2 The variables specific to the training expenditure equation

Given the focus of the analysis on firm-specific knowledge as a source of comparative advantage, I introduced into the *TR* equation a dummy accounting for the implementation of advanced management techniques within a firm during the period 1998–2000 and a dummy accounting for those firms who stated that they had introduced new organisational structures. The first variable was inserted to capture the positive contribution of human resource management practices and of a firm's management skills—resources that are unique, valuable and difficult to imitate—in line with the firm's KBV (i.e. it will enter the *INNO* equation indirectly through the *TR* latent variable). As such, it is expected to enter the equation with a positive sign. Besides, as emphasised in the literature (see, for instance, Antonelli et al. 2010), the propensity to invest in training and the amounts expended can be partly explained by the organisation of knowledge within a firm and by its capacity to introduce and exploit organisational innovations.

Furthermore, I also inserted a dummy to assess the role of universities or other higher education institutions as a source of information for innovation, to explore the idea that skills are complementary to external collaboration strategies (Cohen and Levinthal 1990; Leiponen 2005). In addition, this control made it possible to testing whether or not firms that have established connections with universities are keener to train their staff and if these collaborations contribute to a firm's awareness of the importance of making choices that increase human capital. Therefore, there were no a priori expectations about its sign.

Still another dummy was introduced to account for a lack of qualified personnel as a reason to invest in training. Clearly, spending on R&D-related training is only one possible way to address this shortage, the other being hiring new workers (better educated, better trained, etc.).[16] Besides, I introduced the percentage of employees with tertiary education[17] as a further control.[18] Finally, I have also used a dummy to account for the presence of organisational rigidities within firms during the period 1998–2000, to approximate the need felt by firms to improve the productivity and organisational capabilities of their workers. I expected these latter two dummies to enter the *TR* equation with a positive sign.

3.3.3 The variables specific to the R&D employees equation

Among the variables specific to the *RDpers* equation, there is a dummy that accounts for financial support for innovation activities from local or regional authorities, central government and the European Union (Busom 2000; David et al. 2000; Bérubé and Mohnen 2007). There is also a dummy for firms that identified the existence of organisational rigidities as a factor that hampered innovative activities (Leonard-Burton 1992), giving rise to a need to increase productivity. In both cases, I expected them to have a positive effect on the stock of R&D personnel. In addition, there are controls for those firms that continuously invest in R&D and for firms that cooperated on innovation activities with other enterprises or institutions over the same period (Cohen and Levinthal 1990).[19] These last two dummies were

[16] The choice between the two strategies is likely to be influenced by institutional variables (i.e. the extent of friction in the labour market) and/or depend on the skills supplied by the labour market, on the age of a firm's workers and their education, and on the employment structure of the firm itself (e.g. in terms of the proportion of tenured to temporary jobs).

[17] Unfortunately, this is the only item of information requested in the CIS questionnaire and, given the restrictions operating at the Eurostat Safe Centre, introducing other external controls was been authorised.

[18] I have not used the number of employees with tertiary education for the high correlation with the size control inserted as a common regressor in all the equations of the system.

[19] Many authors find that cooperating firms spend more on R&D (see, for instance, Mairesse and Mohen 2010).

expected to enter the *RDpers* equation with a positive sign, as they were inserted to control for continuous and established R&D activity, namely to account for those firms making an intensive and continuous innovation effort.[20] These firms are likely to develop a larger absorptive capacity, which implies that they can better benefit from knowledge spillovers (Paananen and Kleinknecht 2010), and to systematically exhibit greater numbers of dedicated R&D personnel. More specifically, when spillovers are significant enough (i.e. above a critical level), cooperating firms will spend more on R&D and are increasingly more profitable than non-cooperating enterprises (d'Aspremont and Jacquemin 1988; Kamien et al. 1992; De Bondt 1997; Cassiman and Veugelers 2006).

3.3.4 The variables specific to the innovation output equation

The amount of sales of new products (*INNO*) is explained by two latent variables (*TR** and *RDpers**) and a series of further controls,[21] generally and extensively used in the literature in the field. In particular, given the recent and lively debate on intangible investments (Montresor and Vezzani 2016) and their impact on firms' innovativeness, I inserted (as other intangible sources of competitive advantage) a dummy for those firms that introduced significant changes in their marketing concepts and strategies, and for those firms that implemented significant changes in the aesthetic appearance or design of their products, during the period 1998–2000. I also controlled for those firms that identified their customers or clients as a main source of suggestions for new innovation projects or as major contributors to the implementation of existing projects. The recognition of the needs of potential users or, more precisely, of a potential market for new products or processes involves a process of matching technical possibilities and market opportunities (Freeman and Soete 1997) that is probably fundamental for innovation success. Furthermore, a dummy accounting for the existence at the end of 2000 of valid patents to protect innovations developed within firms was introduced to account for the direct effect of the level of *appropriability* of innovations developed within firms, which may give rise to temporary monopolies (Cooper and Kleinschmidt 1991), increasing innovative sales.[22] It is worth noting that, to the extent that the two latent variables are significant explanatory regressors of the innovation output of a firm, all the exogenous variables that were found to have a significant effect on the amount of training expenditure and on the number of employees in the R&D department indirectly affected innovative sales also.

[20] Their introduction determines a significant drop in the number of observations, but, given their established relevance and importance, and the fact that their exclusion did not affect the direction or significance of the results, I preferred to leave them in the model.

[21] I did not insert the amount of investment in R&D for two reasons. First, it is highly correlated with the latent *RDpers**, as they are both proxies for the innovation effort of a firm; second, given its endogeneity, this would have required the addition of another equation to the system, which anyway would not have solved the correlation issue with the main variable of interest.

[22] As this variable may be endogenous, further checks have been performed. Overall, its inclusion or exclusion does not affect the robustness of the results.

To address whether *ceteris paribus* investments in training and in R&D personnel have the same returns in terms of innovative sales in knowledge-intensive and non-knowledge-intensive firms, instead of inserting the two latent variables *TR** and *RDpers**, I inserted two interaction terms for each of them (latent training in knowledge-intensive firms, *training KIA*; latent training in non-knowledge-intensive firms, *training nonKIA*; latent R&D personnel in knowledge-intensive firms, *lnrdper KIA*; and latent R&D personnel in non-knowledge-intensive firms, *lnrdper nonKIA*) and a dummy to identify knowledge-intensive firms (*dummyKIA*). The same was done for SMEs and non-SMEs (*training sme*, *training big*, *lnrdper sme*, *lnrdper big*). To assess whether returns on investments in training and in R&D employees differ according to firm size and knowledge intensity, an F-test on linear restrictions on coefficients was performed.

4 Econometric analysis: results

In the following section, I will comment on the results obtained for the reference model, reported in Table 4. More specifically, I will comment on the average marginal effects of the variables of interest obtained following the McDonald–Moffit decomposition. In fact, unlike traditional regression coefficients, the Tobit coefficients cannot be interpreted directly as estimates of the magnitude of the marginal effects of changes in the explanatory variables on the expected value of the dependent variable. In a Tobit equation, each marginal effect includes the influence of the explanatory variable both on the probability of adoption and on the intensity of adoption. Therefore, the total (marginal) effect takes into consideration that a change in an explanatory variable will affect simultaneously the number of firms introducing new products into the market and the amount of innovative sales by both current innovators and new innovators. According to the McDonald–Moffit decomposition, the total marginal effect of a change in an independent variable on the expected value of the amount of innovative sales is equal to a weighted sum of: (1) the change in the probability of introducing a new product into the market (by non-product innovators), (2) the change in the amount of innovative sales for firms that have already introduced a new product into the market and (3) the change in the probability of introducing a new product into the market on 100% of the firms.[23] Besides, although for continuous variables marginal effects can be interpreted as elasticities, for dummy variables they represent changes in the predicted probabilities for unit change from a status of 0 to a status of 1.

Not surprisingly, the *TR* equation estimates (Table 4) showed that firm's structural characteristics are highly significant: both a firm's size and belonging to a group entered the equation with the expected positive sign. Lynch (1993) argues that, in small firms, fixed costs of training are distributed across a smaller number of employees, and that the production losses associated with a worker being away from

[23] In other words, McDonald and Moffit (1990) showed that a change in the independent variable x has two effects: it affects the conditional mean of y in the positive part of the distribution (2), and it affects the probability that the observation will fall in that part of the distribution (1). The sum of both effects gives the unconditional effect (3).

the workplace are greater in smaller firms than in larger ones.[24] In addition, firms have higher than average training activities when:

1. they introduce advanced management strategies for which they have to train their managers;
2. they lack qualified personnel (and probably find it more convenient to train existing staff than to hire new employees);
3. they change their organisation;
4. they introduce a different product design;
5. universities are one of their sources of information (i.e. probably as providers of training);
6. and they have a higher than average proportion of tertiary-educated workers (although the corresponding marginal effect is relatively small).

As far as the decision to hire R&D personnel is concerned, if the structural characteristics of the firm are taken into account, the results confirm that the larger the firm, the larger its R&D-related workforce, and that belonging to a high-tech or medium–high-tech manufacturing sector (or to a service sector) significantly increases a firm's number of R&D employees. The results also confirm that the two indicators of a firm's degree of involvement in R&D activities during the period 1998–2000—continuously investing in R&D and cooperating on innovation activities with other enterprises or institutions—are significant explanatory variables for the stock of R&D-related human capital and enter the equation with the expected positive sign. Perhaps unexpectedly, firms belonging to a group do not hire more R&D workers than the average.

As far as the determinants of the *INNO* equation are concerned, the results confirm the positive impact that 'innovation driven' expenditures on training and on staff employed in R&D activities have on firms' innovative sales. In line with the theoretical conclusions of both the economic- and the management-oriented literatures on human capital, investing in training your employees in the development and/or introduction of innovations, as well as hiring skilled employees specifically to carry out R&D activities fosters firms' competitive advantage. More particularly, a 1% increase in training expenditure is associated with a 0.27% increase in innovative sales. Furthermore, a 1% increase in the number of R&D personnel leads to a 3.9% increase of innovative sales.

If we compare the returns on expenditures on training directly aimed at the introduction of new products in knowledge-intensive firms and in non-knowledge-intensive firms (Table 5), the returns do not statistically differ from each other. In addition, contrary to what was initially expected, and in line with the results of the F-test for training expenditures, there is no significant difference between returns on expenditures on R&D personnel in knowledge-intensive and in non-knowledge-intensive enterprises. That is to say, the innovation ability of firms with a relatively high proportion of tertiary-educated workers does not seem to lead to more 'valuable' innovations. However, this finding may be partly due to the fact that the

[24] Another example of a fixed cost associated with the provision of training would be, for example, the cost associated with the design of a training plan or the evaluation of a firm's training needs.

Table 5 The impact of training and R&D personnel on new to the market product sales in knowledge-intensive versus non-knowledge-intensive firms and in SMEs versus non-SMEs

Variables	INNO	INNO
training_KIA	0.292*** (0.0847)	
training_nonKIA	0.272*** (0.0761)	
lnrdper_KIA	4.952*** (0.222)	
lnrdper_nonKIA	4.238*** (0.204)	
training_sme		0.296*** (0.0792)
training_big		0.226** (0.0891)
lnrdper_sme		3.490*** (0.228)
lnrdper_big		5.554*** (0.332)
dummyKIA	–0.120* (0.504)	
sme		3.662*** (0.868)
Clients as source of information	2.769*** (0.236)	2.732*** (0.252)
New design (aesthetic changes)	2.772*** (0.194)	2.621*** (0.134)
New marketing concepts/strategies	2.520*** (0.198)	2.836*** (0.211)
Firm's size	1.669*** (0.125)	1.684*** (0.235)
Group	0.345 (0.216)	−1.838*** (0.159)
High-tech	1.741 (1.086)	0.393* (0.237)
Medium-high-tech	1.843* (1.038)	0.815 (1.271)
Medium-low-tech	2.717*** (1.036)	0.577 (1.222)
Low-tech	2.856*** (1.029)	1.612 (1.218)
Electricity	−3.030** (1.315)	1.632 (1.213)
Market service low	2.284** (1.064)	−4.491*** (1.522)
Financial services	0.240 (1.156)	1.247 (1.245)
Market service high	−1.714* (1.164)	−0.387* (1.345)
Constant	10.93*** (0.0852)	10.77*** (0.0922)
Wald Chi^2 (41)	888,387.56	616,786.15
AIC	21,565.75	23,530.50
BIC	21,814.45	23,776.70
Observations	17,495	17,490

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. High-tech, NACE 30 + 32 + 33; Medium-high-tech, NACE 24 + 29 + 31 + 34 + 35; Medium-low-tech, NACE 23 + 25 + 26 + 27 + 28; Low-tech, NACE 15 + 16 + 17 + 18 + 19 + 20 + 21 + 22 + 36 + 37; Electricity, NACE 40 + 41; Financial services, NACE 65 + 66 + 67; High-tech services, NACE 64 + 72 + 73; Low-tech services, NACE 50 + 51 + 60 + 63. Other controls: 22 country dummies

proxy used captures differences in the skills *acquired* by the workforce and not in the skills *used* by the workforce.

Table 5 reports the results obtained when the interaction terms were introduced into the *INNO* equation to control for differences in returns on expenditures on training and on R&D personnel in knowledge-intensive and non-knowledge-intensive firms, as well as for size effects. When the impact of expenditures on training and on R&D personnel is assessed for SMEs (Table 5), the F-test suggests that returns in SMEs and in large firms are statistically different and greater in larger firms, in line with the theoretical expectations. Furthermore, although in the case of training expenditures these differences are small, in the case of R&D human capital they are quite pronounced: the impact that hiring extra R&D personnel has on innovative sales is almost 80% greater in large firms, confirming the existence of increased returns on this kind of investment and of a competitive advantage resulting from the scale of production. These findings may suggest that the socialisation of knowledge (i.e. knowledge diffusion) is larger and easier in larger firms and that, given the structural nature of training expenditures, their relevance is less affected by the scale of production, as they are not 'production-related' investments. Returns on R&D employees, and more generally on R&D expenditures, on the other hand, may be affected more significantly by the scale of production and by the existence of complementary resources, such as structured marketing and design departments, that are more likely to be found in larger firms.

In line with this, the results also suggest that a firm's capacity to deploy creativity in user direction and to sell its products depends on whether it has introduced new marketing strategies and on whether it has modified the aesthetic appearance of products; furthermore, user-driven innovation enhances a firm's ability to sell its new products. These 'intangibles' have a positive and significant impact on innovative sales, confirming that they are necessary when launching a new product or developing a new brand (Corrado et al. 2005, p. 28).

5 Conclusions and policy implications

It is commonly thought that firms that adopt technologies and, concomitantly, invest in upgrading skills are expected to overperform in comparison with others that do not. In line with this expectation, the empirical evidence presented in this study confirms a positive correlation between the introduction of new products, a firm's expenditure on training and its stock of human capital. This suggests that innovative firms need to integrate their new technologies within their organisation, upgrade the skill level of their workforce and invest in skilled human capital.

However, the econometric analysis does not confirm the existence of statistically significant differences in the returns on investments in training and in R&D personnel between more and less knowledge-intensive firms. Results seem to suggest that there is not a need for an established and already existing stock of human capital to exploit an investment in training and in skilled labour: these investments are vital also for firms starting from scratch. However, given that the use of the proportion of a firm's workers who have a tertiary education might not add much, as a proxy for human capital, to the R&D personnel variable (as, for instance, it does not capture differences in the skills used by the workforce), this aspect needs further investigation.

Moreover, returns on training are only slightly larger in large firms than in SMEs, suggesting that smaller and larger firms obtain nearly the same advantage in terms of innovation output from this kind of investment. This is not the case for returns on R&D personnel: they are statistically significantly larger in large firms than in

SMEs. Stated simply, returns on R&D employees are influenced by the scale of production more than returns on training are: the impact that hiring extra R&D personnel has on innovative sales is almost 80% larger for large firms. This is in line with the expectation that, by spreading the outcome of their projects over a larger amount of output, bigger firms can obtain larger returns from R&D than smaller enterprises (Cohen and Klepper 1996). Furthermore, the smaller difference between SMEs and large firms in terms of observed returns on training expenditures might be partly due to the structural nature of training investments, which are less influenced by the scale of production than R&D-oriented investments.

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