Small Bus Econ (2009) 33:13–33
DOI 10.1007/s11187-009-9184-8

Innovation and productivity in SMEs: empirical evidence for Italy

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Accepted: 1 February 2009 / Published online: 9 May 2009

Abstract Innovation in SMEs exhibits some peculiar features that most traditional indicators of innovation activity do not capture. Therefore, in this paper, we develop a structural model of innovation that incorporates information on innovation success from firm surveys along with the usual R&D expenditures and productivity measures. We then apply the model to data on Italian SMEs from the "Survey on Manufacturing Firms" conducted by Mediocredito-Capitalia covering the period 1995–2003. The model is estimated in steps, following the logic of firms' decisions and outcomes. We find that international competition fosters R&D intensity, especially for high-tech firms. Firm size and R&D intensity, along with investment in equipment, enhances the likelihood of having both process and product innovation. Both these kinds of innovation have a positive impact on firm's productivity, especially process innovation. Among SMEs, larger and older firms seem to be less productive.

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Keywords R&D · Innovation · Productivity · SMEs · Italy

JEL Classifications L26 · L60 · O31 · O33

1 Introduction

In the past decade, labor productivity growth in Italy has been one of the lowest in the EU; low growth has been particularly strong in manufacturing, where the growth rate even turned negative in the period from 2000 to 2005 (see Fig. 1). Such a poor performance raises unavoidable policy concerns about the underlying reasons for it. Is the labor productivity slowdown due to the decline in total factor productivity

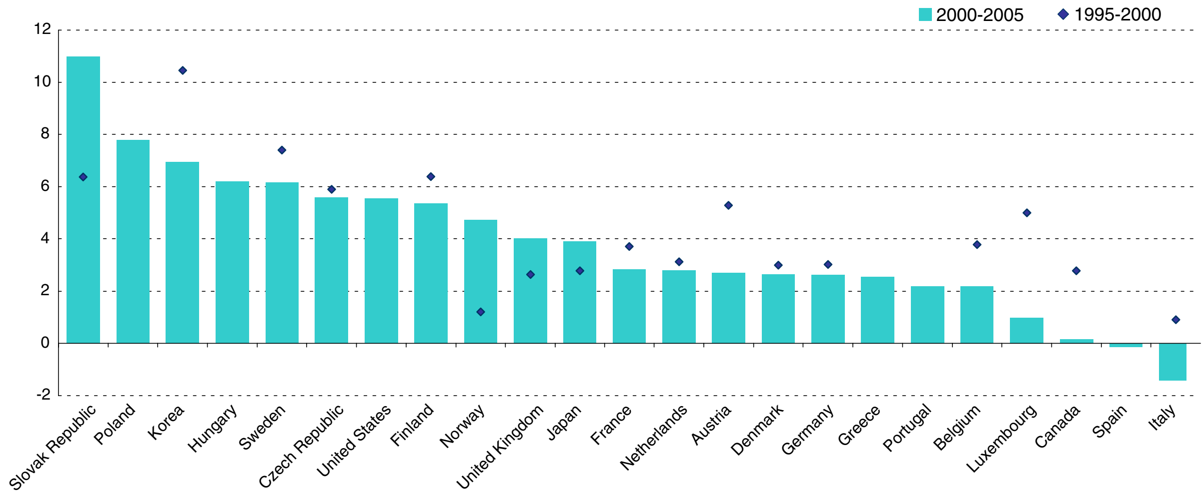

Fig. 1 Value added per employee. Percentage change, annual rate (1995–2000 and 2000–2005). Total manufacturing. *Source*: OECD Factbook, April 2008. Permanent link http://dx.doi.org/10.1787/271772787380

(see Daveri and Jona-Lasinio 2005)? Or, more precisely, is it a consequence of the exhaustion of the so-called "capital deepening" phase that supported labor productivity growth during the 1980s (as documented by Pianta and Vaona 2007)? Alternatively, is it simply due to input reallocation following a change in the relative price of labor with respect to capital after the labor market reforms of the early 1990s (Brandolini et al. 2007)? Or does the explanation lie in the evergreen motto that Italian firms exhibit insufficient R&D investment (European Commission 2006)?

The latter aspect has been largely explained by the unquestionable fragmentation of the Italian production system. According to the latest available data from the Census, more than 99% of active firms (out of 4 million) have fewer than 250 employees (95% have fewer than 10 employees, see Fig. 2). If there were a positive relationship between innovation activity—including R&D—and firm size, the size distribution of Italian firms could help to explain why Italy is lagging behind in terms of aggregate R&D investment.

Nevertheless, many scholars have argued that small firms are the engines of technological change and innovative activity, at least in certain industries (see the series of works by Acs and Audretsch 1988, 1990). But at the same time, innovation in small and medium enterprises exhibits some peculiar features that most traditional indicators of innovation activity would not capture, incurring the risk of underestimating their innovation effort. In fact, innovation often occurs without the performance of formal R&D, and this is particularly true for SMEs. Despite the existence of a large number of policies designed to promote and facilitate the operation of the innovation process within SMEs, especially in Italy, the knowledge about how SMEs actually undertake innovative activities remains quite limited, causing a significant bias in the treatment of the R&D-innovation relationship (see Hoffman et al. 1998 for a literature review on this topic in the UK).

This paper is not an attempt to verify or disprove the Schumpeterian hypothesis, i.e., to study the relationships between firm size and innovative activity at the firm level; instead it investigates how and when innovation takes place in SMEs and whether—and how—innovation outcomes impact SME firms' productivity. We caution the reader that because we rely mainly on dummy variables for the presence of innovation success, we are in fact unable to say very much about the size-innovation relationship per se. In general, larger firms have more than one innovative activity, which implies a higher probability that at least one of them is successful and that the innovation dummy is one.

The remainder of the paper is organized as follows. In Sect. 2 we put our modeling approach

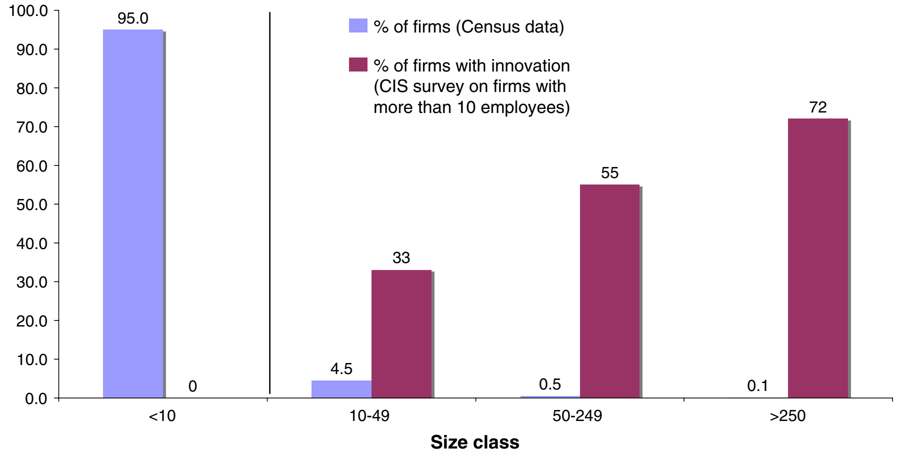

Fig. 2 Size distribution of Italian firms (2001) and share of firms with innovation by size class (2002–2004). *Source*: National Institute of Statistics (ISTAT). Census of Manufacturing and Services (2001) for the size distribution. Community innovation survey (CIS) for the presence of innovation activity (2002–2004)

and our results into perspective by giving a summary—far from being exhaustive—of the previous empirical studies on the R&D innovation-productivity relationships. In Sect. 3, we first explain our data and how we bring them into play in our modeling approach; we then present in turn our main results on the R&D investment equations, the innovation equations and the productivity equation; finally, we discuss and give evidence on the robustness of these results and compare them to the comparable findings of Griffith et al. (2006). In Sect. 4 we conclude with a discussion of the results and with directions for further research.

2 Previous studies of the innovation-productivity link

Measuring the effects of innovative activities on firms' productivity has been an active area for research for several decades, both as a policy concern and as a challenge for econometric applications. The large number of empirical studies available notwithstanding, measuring the effect of innovation (product and process) on productivity at the firm level (see Griliches 1995), the literature still does not provide a unique answer in terms of the magnitude of this impact. Because of the variability and uncertainty that is inherent in innovation, this fact is not unexpected: at best, economic research should give us a distribution of innovation outcomes and tell us how they have changed over time. Recent firm level studies, including Lichtenberg and Siegel (1991) on the US, Hall and Mairesse (1995) and Mairesse and Mohnen (2005) on France, Harhoff (1998) and Bönte (2003) on Germany, Klette and Johansen (1996) on Norway, Van Leeuwen and Klomp (2006) on The Netherlands, Janz et al. (2004) on Germany and Sweden, Lööf and Heshmati (2002) on Sweden, Lotti and Santarelli (2001) and Parisi et al. (2006) on Italy, find that the effect of R&D on productivity is positive,[1] although some have suggested that the returns to R&D have declined over time (Klette and Kortum 2004). The majority of the empirical analyses rely on an extended production-function approach, which includes R&D (or alternative measures of innovation effort) as another input to production.

However, it is widely recognized that R&D does not capture all aspects of innovation, which often occurs through other channels. This is particularly true for small and medium-size firms and could lead to a severe underestimation of the impact of innovation on productivity. In order to overcome this problem, subsequent studies have moved from an input definition of innovation activities to an *output approach*, by including in the regressions the outcome of the innovation process rather than its input. The rationale behind this line of reasoning is simple: if it is not possible to measure the innovative effort a firm exerts because of the presence of latent and unobservable variables, one should look at the results of R&D investment: training, technology adoption and sales of products new to the market or the firm.

[1] For a survey of previous empirical results, see Mairesse and Sassenou (1991); Griliches (1998).

All these activities may be signs of successful innovative effort, but if one considers R&D only, a lot of this informal activity is going to be missing from the analysis (Blundell et al. 1993, Crépon et al. 1998). As suggested by Kleinknecht (1987), official R&D measures for SMEs may underestimate their innovation activities, and the underestimate is likely to be larger at the left end of the firm size distribution.

Crépon et al. (1998) take a further step in this literature, combining the aforementioned approaches. They propose and estimate a model—CDM model hereafter—that establishes a relationship among innovation input (mostly, but not limited, to R&D), innovation output and productivity. This structural model allows a closer look at the black box of the innovation process at the firm level: it not only analyzes the relationship between innovation input and productivity, but it also sheds some light on the process in between the two.

The CDM approach is based on a simple three-step modeling of the logic of firms' innovation decisions and outcomes. The first step corresponds to the firm decision whether to engage in R&D or not and on how many resources to invest. Given the firm's decision to invest in innovation, the second step consists of a knowledge production function (as in Pakes and Griliches 1984), which relates innovation output to innovation input and other factors. In the third step, an innovation augmented Cobb-Douglas production function specifies the effect of innovative output on the firm's productivity. The model is tailored to take advantage of innovation survey data, which provide measures of other aspects of innovation and not only on R&D expenditures. Given the increased diffusion of this type of micro data across countries and among scholars, many empirical explorations of the impact of innovation on productivity have relied on the CDM framework.[2]

In particular, Parisi et al. (2006) apply a modified version of the CDM model to a sample of Italian firms (using two consecutive waves of the Mediocredito-Capitalia survey, the same source we are using in our empirical analysis), enriching the specification with a time dimension.[3] They find that process innovation has a large and significant impact on productivity and that R&D is positively associated with the probability of introducing a new product, while the likelihood of having process innovation is directly linked to a firm's investment in fixed capital. In comparing those results to the ones we obtain in this paper, one has to keep in mind that, due to the design of the survey itself, the panel used by Parisi, Schiantarelli and Sembenelli is tilted towards medium and large firms much more than the original Mediocredito-Capitalia sample.

To our knowledge, none of the empirical papers investigating the relationship between innovation and productivity has dealt specifically with small and medium-sized firms. On one hand, this paper is aimed at filling this gap, since innovation in SMEs is even more difficult to measure; on the other, like Griffith et al. (2007), we try to improve on the CDM original specification by considering separately both product and process innovation.

3 Data and main results

3.1 Descriptive statistics

The data we use come from the seventh, eighth and ninth waves of the "Survey on Manufacturing Firms" conducted by Mediocredito-Capitalia (an Italian commercial bank). These three surveys were carried out in 1998, 2001 and 2004, respectively, using questionnaires administered to a representative sample of Italian manufacturing firms. Each survey covered the 3 years immediately prior (1995–1997, 1998–2000, 2001–2003), and although the survey questionnaires were not identical in all three of the surveys, the questions providing the information used in this work were unaffected. All firms with more than 500 employees were included, whereas smaller firms were selected using a sampling design stratified by geographical area, industry and firm size. We

[2] See Hall and Mairesse (2006) for a comprehensive survey. Recent papers based on the CDM model include Benavente (2006) on Chile, Heshmati and Lööf (2006) on Sweden, Jefferson et al. (2006) on China, Klomp and Van Leeuwen (2001) on The Netherlands, Mohnen et al. (2006) on seven European countries and Griffith et al. (2006) on four European countries.

[3] Although the Mediocredito-Capitalia survey is not a panel itself, it contains repeated observation for a number of firms, which is enough to allow the estimation of a dynamic framework. See Sect. 3 of this paper for further information on the data.

merged the data from these three surveys, excluding firms with incomplete information or with extreme observations for the variables of interest.[4] We focus on SMEs, which represent nearly 90% of the whole sample, imposing a threshold of 250 employees, in line with the definition of the European Commission; we end up with an overall unbalanced panel of 9,674 observations on 7,375 firms, of which only 361 are present in all three waves. Table 1 contains some descriptive statistics for both the unbalanced and the balanced panel. Not surprisingly, in both cases, the firm size distribution is skewed to the right, with an average of respectively 50 and 53 employees and a median of respectively 32 and 36. Firms in the low-tech sector tend to be slightly smaller, with average employment of 47 and median employment of 30 (Table 2).[5] In the unbalanced sample, 62% of the firms have successful product and/or process innovation, but only 41% invest in R&D. Such a difference is evidence for the importance of informal innovation activities. Although a sizeable share of firms invests in R&D, only a small fraction seems to do it continuously: out of 361 firms in our balanced panel, 34% invested in R&D in every period under examination. For 21% of the firms, product and process innovations go together, while 27% are process innovators only. Concerning competition, more than 42% of the firms in the sample have national competitors, while 18% and 14% have European and international competitors, respectively. Interestingly, low-tech firms tend to compete more within the national boundaries, while almost half of the high-tech firms operate in European or international markets, in line with Janz et al. (2004).

For comparability with the samples used by Griffith et al. (2006) for France, Germany, Spain and the UK, in Table 7 of the Appendix we show the means for our entire sample, including non-SMEs and excluding firms with fewer than 20 employees. Even if the share of innovators—product and process—are not dissimilar, Italian firms display a significantly lower R&D intensity but roughly comparable investment intensities. These figures can be partially explained by the different firm size distribution within each country: around 60 of the firms in the Italian sample for the year 2000 belong to the smaller class size (20–49 employees), a figure much larger than that for other countries.[6] Interestingly, labor productivity is somewhat higher for the Italian firms.

3.2 Data and model specification

As discussed earlier, in order to analyze the relationship among R&D, innovation and productivity at the firm level, we relied on a modified version of the model proposed by Crépon et al. (1998). This model—specifically tailored for innovation survey data and built to take into account the econometric issues that arise in this context—is made up of three building blocks, following the sequence of firms' decisions in terms of innovation activities and outcomes. The first one concerns R&D activities, i.e., the process that leads the firm to decide whether to undertake R&D projects or not and how much to invest on R&D. The second one consists of a two-equation knowledge production function in which R&D is one of the inputs, and process and product innovation are two outputs. The third consists of a simple extended production function in which knowledge (i.e., process and product innovation) is an input.

We perform our analysis for the whole sample of firms, and for high- and low-tech firms, since the effect of R&D on productivity can vary a lot with the technological content of an industry (see Verspagen 1995 for a cross-country, cross-sector study and,

[4] We require that sales per employee be between 2,000 and 10 million euros, growth rates of employment and sales of old and new products between −150% and 150%, and the R&D employment share less than 100%. We also replaced R&D employment share with the R&D to sales ratio for the few observations where it was missing. For further details, see Hall et al. (2008). In addition, we restrict the sample by excluding a few observations with zero or missing investment.

[5] We adopt the OECD definition for high- and low-tech industries. *High-tech industries* encompass high and medium-high technology industries (chemicals; office accounting and computer machinery; radio, TV and telecommunication instruments; medical, precision and optical instruments; electrical machinery and apparatus, n.e.c.; machinery and equipment; railroad and transport equipment, n.e.c.). *Low-tech industries* encompass low and medium-low technology industries (rubber and plastic products; coke, refined petroleum products; other non-metallic mineral products; basic metals and fabricated metal products; manufacturing, n.e.c.; wood, pulp and paper; food, beverages and tobacco products; textile, textile products, leather and footwear).

[6] We do not yet know how much of the difference is due to differences in sampling strategy across the different countries.

Table 1 Descriptive statistics, unbalanced and balanced sample

Period: 1995–2003	Unbalanced sample	Balanced sample
Number of observations (firms)	9,674 (7,375)	1,083 (361)
Continuous R&D engagement (%)	41.49	26.04
R&D intensity (for R&D doing firms, in logs)[a]	1.08	1.02
Innovator (process and/or product, %)	62.05	66.39
Process innovation (%)	50.75	53.65
Product innovation (%)	34.85	40.63
Process and product innovation (%)	20.94	25.39
Process innovation only (%)	27.21	25.76
Share of sales with new products (%)	22.16	22.98
Labor productivity: mean/median[a]	4.99/4.94	4.94/4.85
Investment intensity: mean/median[a]	7.90/4.05	6.92/4.01
Public support (%)	45.49	50.51
Regional competitors (%)	16.84	14.87
National competitors (%)	42.24	41.37
European competitors (%)	17.53	18.10
International (non EU) competitors (%)	13.56	17.17
Large competitors (%)	36.18	34.16
Percentage of firm in size class (11–20)	30.04	19.67
Percentage of firm in size class (21–50)	38.85	44.04
Percentage of firm in size class (51–250)	31.11	36.29
Percentage of firm in age class (<15 years)	32.45	24.10
Percentage of firm in age class (15–25 years)	30.48	31.12
Percentage of firm in age class (>25)	37.07	44.78
Number of employees: mean/median	49.45/32	53.48/36
Group (%)	20.07	16.25

[a] Units are logs of euros (2000) per employee

more recently, an analysis based on micro data by Potters et al. 2008).

Because of the way our data, and innovation survey data in general, were collected, our analysis here is essentially cross-sectional. Although there are three surveys covering 9 years, the sampling methodology was such that few firms appeared in more than one survey (as we saw in Table 1, fewer than 5% of the firms and about 10% of the observations are in the balanced panel). Due to the resulting small sample size and very limited information in the time series dimension, we found that controlling for fixed firm effects was not really possible in practice. Other difficulties arise from the fact that the process and product innovation indicators are defined over 3-year periods, while the income statement data, when available, are on a yearly basis. As a robustness check we estimated the same three-equation model using lagged R&D intensity instead of contemporaneous R&D intensity in order to account for a plausible delay between R&D and innovation output. Given the low volatility of R&D investment over time, the results were very similar to those reported below.[7]

3.3 The R&D equations

The firm R&D decisions can be modeled in terms of two equations: a selections equation and an intensity equation. The selection equation can be specified as:

$$\mathrm{RDI}_i = \begin{cases} 1 & \text{if} \quad \mathrm{RDI}_i^* = w_i\alpha + \varepsilon_i > \bar{c} \\ 0 & \text{if} \quad \mathrm{RDI}_i^* = w_i\alpha + \varepsilon_i \leq \bar{c} \end{cases} \qquad (1)$$

where RDI_i is an (observable) indicator function that takes value 1 if firm i has (or reports) positive R&D

[7] Although we did not include these results in the paper for the sake of brevity, they are available from the authors.

Table 2 Descriptive statistics, high-tech and low-tech industries

Period: 1995–2003	High-tech firms	Low-tech firms
Number of observations (firms)	2,870 (2,165)	6,804 (5,210)
Continuous R&D engagement (%)	58.75	34.22
R&D intensity (for R&D doing firms, in logs)[a]	1.20	0.98
Innovator (process and/or product, %)	69.41	58.95
Process innovation (%)	54.25	49.28
Product innovation (%)	43.80	31.06
Process and product innovation (%)	25.57	18.72
Process innovation only (%)	26.20	27.90
Share of sales with new products (%)	22.63	21.88
Labor productivity: mean/median[a]	4.93/4.89	5.02/4.96
Investment intensity: mean/median[a]	6.22/3.36	8.62/4.38
Public support (%)	46.27	45.16
Regional competitors (%)	12.30	18.75
National competitors (%)	36.45	44.68
European competitors (%)	25.40	14.21
International (non EU) competitors (%)	19.86	10.91
Large competitors (%)	42.54	33.50
Percentage of firm in size class (11–20)	27.25	31.22
Percentage of firm in size class (21–50)	36.86	39.68
Percentage of firm in size class (51–250)	35.89	29.10
Percentage of firm in age class (<15 years)	32.79	32.30
Percentage of firm in age class (15–25 years)	31.67	29.98
Percentage of firm in age class (>25)	35.54	37.71
Number of employees: mean/median	54.17/35	47.46/30
Group (%)	25.26	17.89

[a] Units are logs of euros (2000) per employee

expenditures, RDI_i^* is a latent indicator variable such that firm i decides to perform (or to report) R&D expenditures if they are above a given threshold $\bar{c}$, w_i is a set of explanatory variables affecting R&D and ε_i the error term.

The R&D intensity equation can be specified as:

$$\mathrm{RD}_i = \begin{cases} \mathrm{RD}_i^* = z_i\beta + e_i & \text{if} \quad \mathrm{RDI}_i = 1 \\ 0 & \text{if} \quad \mathrm{RDI}_i = 0 \end{cases} \qquad (2)$$

where RD_i^* is the unobserved latent variable accounting for firm's innovative effort, and z_i is a set of determinants of R&D expenditures. Assuming that the error terms in (1) and (2) are bivariate normal with zero mean and variance equal to unity, the system of Eq. 1 and 2 can be estimated by maximum likelihood. In the literature, this model is sometimes referred to as a Heckman selection model (Heckman 1979) or Tobit type II model (Amemiya 1984).

Before estimating the selection model, we performed a non-parametric test for the presence of selection bias in the R&D intensity equation (see Das et al. 2003; Vella 1998 for a survey). In so doing, we first estimate a probit model in which the presence of positive R&D expenditures is regressed on a set of firm characteristics: firm size, age and their squares, a set of dummies indicating competitors' size and location, dummy variables indicating (1) whether the firm received government subsidies and (2) whether the firm belongs to an industrial group; the results are reported in Table 8 in the Appendix. From this result, we recovered for each firm the predicted probability of having R&D and the corresponding Mills' ratio, and then we estimated a simple linear regression (by OLS) for R&D intensity, including in this regression the predicted probabilities from the R&D decision equation, the Mills' ratio, their squares and interaction terms. The presence of selectivity bias is tested for by looking at the significance of those "probability terms."[8] The results are reported in Table 8 in the Appendix. As one can see, the probability terms are never significant, either singly or jointly. Therefore, we adopted the linear regression (OLS) specification for the R&D intensity decision without any correction for selectivity bias. In Table 3 we report the estimates performed using the pooled overall high- and low-tech samples, and including the regression year and two-digit industry dummies as well as "wave dummies" as controls. Wave dummies are a set of indicators for firm's presence or absence in the three waves of the survey.[9]

Table 3 shows that the presence of EU and international competitors is strongly positively related to R&D effort: engaging in exporting activity implies investing more in R&D (see Baldwin et al. 2002 and Baldwin and Gu 2003 for an exploration using Canadian data), and this effect is particularly strong for high-tech firms, where competing internationally is associated with a doubling of R&D intensity. Non-exporting firms, i.e., those operating in a market that is mainly local, have, on average, lower R&D intensity.

We also found that having received a subsidy significantly boosts R&D intensity, as could be expected.[10] Being part of an industrial group increases R&D intensity, but the coefficient is barely statistically significant.

We also included age class dummies in the regression (the base group is younger firms, defined as those with fewer than 15 years): although the coefficients are not statistically significant, they seem to indicate that older firms may have a slightly lower incentive to do R&D than younger firms. We find also that "other things being equal," larger firms tend to do relatively less R&D per employee than small firms (the 11–20 size class), and this is particularly true for low-tech firms (for a discussion of the relationship between size and R&D investment at the firm level, see Cohen and Klepper 1996).

3.4 Innovation equations

In order to account for firm innovations that are not necessarily based on formal R&D activities, which are likely to be especially important for SMEs, we do not restrict estimation to R&D performing firms only. Following the original CDM model, we thus specify the innovation equation in terms of the latent R&D intensity variable and not the observed R&D intensity. Also, like in Griffith et al. (2006), we specify separately an equation for product innovation and one for process innovation, which can thus be written as:

$$\begin{cases} \mathrm{PROD}_i = \mathrm{RD}_i^* \gamma + x_i \delta + u_{1i} \\ \mathrm{PROC}_i = \mathrm{RD}_i^* \gamma + x_i \delta + u_{2i} \end{cases} \tag{3}$$

where RD_i^* is the latent innovation effort proxied by the predicted value of R&D intensity from the first step model, x_i a set of covariates and u_{1i} and u_{2i} the error terms such that $\mathrm{Cov}(u_{1i}, u_{2i}) = \rho$. Including the predicted R&D intensity in the regression accounts for the fact that all firms may have some kind of innovative effort, although only some of them invest in R&D and report it. Using the predicted value instead of the realized value is also a sensible way to instrument the innovative effort in the knowledge production function in order to deal with the simultaneity problem between R&D effort and the expectation of innovative success.

Equation 3 is estimated as a bivariate probit model, assuming that most of the firm characteristics that affect product and process innovation are the same, although of course their impacts may differ. The only exception is the investment rate, which is assumed to be related to process innovation but not to product innovation. Table 4 (as in Table 3) reports the results from the overall, and the high-tech and low-tech sample. The estimated correlation coefficient ρ is always positive and significant, which implies that process and product innovation are influenced to some extent by the same unobservable factors. Marginal effects are reported in square brackets. For an example of how to interpret these effects, the first two columns indicate that a doubling

[8] Note that this is a generalization of Heckman's two-step procedure for estimation when the error terms in the two equations are jointly normally distributed. The test here is valid even if the distribution is not normal.

[9] For instance, a firm present in all three waves will have a "111" code, "100" if present in the first only, "110" if in the first and in the second only, and so forth. These codes are transformed into a set of six dummies ($2^3 = 8$ minus the 000 case and the exclusion restriction).

[10] Because of the large number of missing observations, we could not use a narrower definition of subsidies.

Table 3 R&D intensity (STEP 1): OLS model (dependent variable, R&D intensity)

R&D expenditure per employee (in logarithms)	All firms	High tech	Low tech
D (Large firm competitors)	0.062	0.197	−0.028
	(0.073)	(0.109)	(0.098)
D (Regional competitors)	0.094	0.548	−0.049
	(0.167)	(0.320)	(0.197)
D (National competitors)	0.138	0.638*	−0.037
	(0.147)	(0.290)	(0.172)
D (European competitors)	0.511***	0.834**	0.448*
	(0.154)	(0.287)	(0.187)
D (International competitors)	0.570***	1.034***	0.357
	(0.159)	(0.296)	(0.195)
D (Received subsidies)	0.389***	0.619***	0.213*
	(0.072)	(0.111)	(0.095)
D (Member of a group)	0.198*	0.247	0.165
	(0.084)	(0.128)	(0.114)
Size class (21–50 employees)	−0.271**	−0.141	−0.349**
	(0.104)	(0.164)	(0.134)
Size class (51–250 employees)	−0.271*	−0.123	−0.379**
	(0.109)	(0.167)	(0.145)
Age class (15–25 years)	−0.009	0.032	−0.032
	(0.094)	(0.141)	(0.127)
Age class (>25 years)	−0.061	−0.147	−0.003
	(0.090)	(0.135)	(0.120)
R^2	0.061	0.065	0.038
Number of observations	4,015	1,687	2,328

Coefficients and their standard errors are shown

The standard errors are robust to heteroskedasticity and clustered at the firm level

Industry, wave and time dummies are included in all equations

Reference groups: D (provincial competitors); size class (11–50 employees); age class (<15 years)

* Significant at 10%, ** significant at 5%, *** significant at 1%

of predicted R&D intensity is associated with a 0.19 increase in the probability of process innovation and a 0.25 increase in the probability of product innovation.

As expected, the R&D intensity predicted by the first equation has a positive and sizeable impact on the likelihood of having product and process innovation, which is higher for product innovation for all three groups of firms. Interestingly, the impact of R&D on process innovation in low-tech firms is more than double that for high-tech firms (0.24 vs. 0.10). Firms in low-tech industries, on average, have lower R&D intensity, but their R&D effort leads to a higher probability of having at least one process innovation when compared to high-tech firms. A number of interpretations suggest themselves: one possibility is that innovating in this sector takes less R&D because it involves changes to the organization of production that are not especially technology-linked. A second related interpretation is provided by the dual role of R&D (Cohen and Levinthal 1989): investment in research is fundamental for product innovation, but at the same time, it increases firm's ability to absorb and adopt those technologies developed somewhere else, which are likely to become process innovation.

As suggested in the introduction, firm size is strongly associated with innovative success, especially among low-tech firms. Note that this result does not contradict that for R&D intensity, because innovation is measured by a dummy variable. Although larger firms may have a somewhat lower R&D effort given their size, in absolute terms they do more R&D, so they have a higher probability of innovative success. Finally, with the exception of product innovation in firms older than 25 years, the age of the firm is not particularly associated with innovation of either kind.

We also note that investment intensity is positively associated with process innovation in both high- and low-tech firms. We defer a fuller discussion of the

Table 4 A bivariate probit for process and product innovation dummies (STEP 2): all firms, high- and low-tech firms

	All firms		High-tech firms		Low-tech firms	
	(1) Process innovation	(1a) Product innovation	(2) Process innovation	(2a) Product innovation	(3) Process innovation	(3a) Product innovation
Predicted R&D intensity (in logs)	0.483*** [0.193]	0.686*** [0.250]	0.256*** [0.102]	0.499*** [0.196]	0.602*** [0.240]	0.749*** [0.261]
	(0.045)	(0.045)	(0.056)	(0.056)	(0.069)	(0.069)
Investment per employee (in logs)	0.125*** [0.050]		0.120*** [0.047]		0.129*** [0.051]	
	(0.011)		(0.021)		(0.013)	
Size class (21–50 employees)	0.255*** [0.101]	0.310*** [0.115]	0.159* [0.063]	0.126* [0.050]	0.350*** [0.139]	0.431*** [0.153]
	(0.033)	(0.035)	(0.062)	(0.063)	(0.043)	(0.046)
Size class (51–250 employees)	0.446*** [0.175]	0.504*** [0.189]	0.276*** [0.108]	0.299*** [0.118]	0.606*** [0.237]	0.679*** [0.248]
	(0.037)	(0.038)	(0.068)	(0.067)	(0.048)	(0.049)
Age class (15–25 years)	0.009 [0.004]	0.050 [0.018]	0.004 [0.001]	0.036 [0.014]	0.020 [0.008]	0.058 [0.020]
	(0.034)	(0.034)	(0.061)	(0.061)	(0.040)	(0.042)
Age class (>25 years)	−0.003 [−0.001]	0.129*** [0.047]	0.094 [0.037]	0.157* [0.062]	−0.067 [−0.026]	0.094* [0.033]
	(0.033)	(0.034)	(0.062)	(0.062)	(0.039)	(0.041)
Rho	0.400***		0.345***		0.430***	
Pseudo R^2	0.10	0.08	0.09	0.08	0.10	0.06
Number of observations (firms)	9,674 (7,375)		2,870 (2,165)		6,804 (5,210)	

Coefficients, marginal effects and standard errors are shown

Marginal effects are in square brackets

The standard errors are robust to heteroskedasticity and clustered at the firm level

Industry, wave and time dummies are included in all equations

Reference groups: D (provincial competitors), size class (11–50 employees), age class (<15 years)

* Significant at 10%, ** significant at 5%, *** significant at 1%

issues associated with the presence of investment in the process innovation equation (and also in the product innovation equation) until after we present the productivity results.

3.5 The productivity equation

The productivity equation is specified as a simple Cobb–Douglas technology with constant returns to scale, and with labor, capital and knowledge inputs, which can be written as:

$$y_i = \pi_1 k_i + \pi_2 \mathrm{PROD}_i + \pi_3 \mathrm{PROC}_i + v_i \qquad (4)$$

where y_i is labor productivity (real sales per employee, in logs); k_i is investment intensity, our proxy for physical capital; PROD_i and PROC_i are knowledge inputs, proxied by the predicted probability of product and process innovation. Using these predicted probabilities instead of the observed indicators is a way to address the issue of potential endogeneity (and measurement errors in variables) of the knowledge inputs. We thus generate the two predicted probabilities of innovation from the two estimated innovation equations as being respectively the probability of process innovation alone and the probability of product innovation, whether or not it is accompanied by process innovation.[11] Results are reported in Table 5 for specifications with and without investment as a proxy for capital; as before, estimates are reported separately for all firms and for firms in high- and low-tech industries. Our preferred specifications, in columns (1a), (2a) and (3a), include investment intensity.

When investment is not included in the regression, i.e., in columns (1a), (2a) and (3a), process innovation displays a sizeable and positive impact on productivity. Process innovators have a productivity level approximately two and one half times that of non-innovators, *ceteris paribus*. On the contrary, when investment is included, the coefficients of process innovation are not significant. These differences clearly arise from the inclusion of the same investment variable in the process innovation equation with the consequence that process innovation in the productivity equation already encompasses the effect of investment in new machinery and equipment. However, since the investment rate is a better measure than the process innovation dummy, when both variables are included its effect tends to dominate.

Product innovation enhances productivity considerably, although to a lesser extent than process innovation when investment is included in the productivity equation. The impact is slightly stronger for firms in the high-tech firms than in the low-tech industries. Because in particular, much of product innovation is directed towards higher quality products and product differentiation, it is not surprising that it shows up quite differently than process innovation in the productivity relation. Table 9 in the Appendix confirms that the contribution of product innovation to productivity is much more robust to the inclusion of investment intensity in the productivity equation included in the product and process innovation equations.

Another interesting and robust finding is that among SMEs relatively larger firms seem to be significantly less productive than smaller ones. It is also noteworthy that age impacts productivity negatively for firms in the high-tech industries.

3.6 Investment and innovation

In our preferred specification in Table 4, we assumed that capital investment—which to a great extent means the purchase of new equipment—should contribute significantly to process innovation, but not to product innovation. In fact, we found a small marginal impact of investment on process innovation that was approximately the same for high- and low-tech industries (0.05).

Because the assumption that investment is associated with process and not with product innovation may be somewhat arbitrary, we performed some robustness checks reported in Table 9 in the Appendix, experimenting with different alternatives. Columns (1)–(4) of that Table reports all the possible combinations in the second step: whether investment is devoted to process innovation only (column 1), to product innovation only (column 2), to both (column 3) or to none (column 4). In the same columns we show the productivity equation, estimated using each of these different models to predict the probability of process and product innovation. In the bottom panel

[11] The first is estimated probability of process and not product from the bivariate probit model in Table 4, and the second is the marginal probability of product innovation from the same model.

Table 5 Production function (STEP 3): all firms, high- and low-tech firms

Dependent variable: labor productivity (sales per employee in logs)	All firms		High-tech firms		Low-tech firms	
	(1)	(1a)	(2)	(2a)	(3)	(3a)
Predicted probability of process innovation only	2.624***	0.193	2.742***	0.664	2.797***	0.063
	(0.146)	(0.267)	(0.304)	(0.512)	(0.171)	(0.391)
Predicted probability of product innovation	0.961***	0.597***	1.314***	0.700***	0.900***	0.708***
	(0.083)	(0.093)	(0.149)	(0.200)	(0.118)	(0.122)
Investment per employee (in logs)		0.099***		0.073***		0.109***
		(0.010)		(0.015)		(0.015)
Size class (21–50 employees)	−0.184***	−0.136***	−0.140***	−0.085**	−0.204***	−0.163***
	(0.016)	(0.017)	(0.029)	(0.031)	(0.020)	(0.021)
Size class (51–250 employees)	−0.313***	−0.243***	−0.177***	−0.116**	−0.391***	−0.321***
	(0.023)	(0.024)	(0.037)	(0.038)	(0.031)	(0.032)
Age class (15–25 years)	−0.006	−0.017	−0.0579*	−0.064*	0.0174	0.005
	(0.016)	(0.016)	(0.026)	(0.026)	(0.020)	(0.020)
Age class (>25 years)	0.008	−0.038*	−0.0764**	−0.069**	0.0469*	−0.036
	(0.016)	(0.016)	(0.027)	(0.027)	(0.020)	(0.022)
R^2	0.209	0.219	0.194	0.201	0.227	0.226
Number of observations (firms)	9,674 (7,375)		2,870 (2,165)		6,804 (5,210)	

Coefficients and their standard errors are shown

The standard errors are robust to heteroskedasticity and clustered at the firm level

Industry, wave and time dummies are included in all equations

Reference groups: D (provincial competitors); size class (11–50 employees); age class (<15 years)

* Significant at 10%, ** significant at 5%, *** significant at 1%

of the Table, we also report an alternative specification of the productivity equation without investment. Although column (1) still represents our preferred specification, column (3) suggests that physical investment has a small (0.02) positive impact on product innovation as well. Turning to the productivity equation, it can be noted that the inclusion of investment wipes out the significance of process innovation, since investment is one of its main determinants, but not of product innovation, which is more dependent on R&D investment. Excluding investment from the productivity equation reveals that the process innovation associated with investment is more relevant for productivity than predicted product innovation (compare the process innovation coefficients for step 3 in columns 1 and 3).

3.7 Further robustness checks

The estimation method used in the body of the paper is sequential, with three steps: (1) the R&D intensity equation estimated only on firms that report doing R&D continuously; (2) a bivariate probit for process and product innovation that contains R&D predicted by the first step for all firms; (3) a productivity equation that contains the predicted probabilities for process innovation alone and product innovation with or without process innovation. Because the last two steps contain fitted or predicted values, their standard errors will be underestimated by our sequential estimation method. In order to assess the magnitude of this underestimation, we re-estimated our preferred model specification (1a) on all firms simultaneously using maximum likelihood.

The likelihood function consists of the sum of a normal density for the R&D equation, a bivariate probit for process and product innovation, and a normal density for the productivity equation; it does not allow for correlation of the disturbances among the three blocks, although the resulting standard errors are robust to such correlation. In this likelihood function, the equation for R&D is directly entered into the innovation equations and that for innovation probability directly into the productivity equation, so the coefficient standard errors take account of the estimation uncertainty in the first two stages.

The results of estimation on the pooled model are shown in column (2) of Table 10 in the Appendix, with the sequential estimation results in column (1) for comparison.[12] Although the results for the key coefficients are similar and have approximately the same significance, the standard errors from pooled maximum likelihood are considerably larger, especially for the predicted process and product probabilities. So this should be kept in mind when interpreting the results in the tables of the paper.

Table 10 also shows the results of another experiment—in this paper we chose to proxy capital intensity by investment intensity, in order to be comparable to the results in Griffith et al. 2006. However, in our data we also have a measure of capital available, constructed from investment using the usual declining balance method with a depreciation rate of 5% and an initial stock from the balance sheet of the firm in 1995 or the year it entered the survey. Columns (3)–(5) of the table show the results of estimating specifications containing capital stock at the beginning of the period and using the pooled maximum likelihood method. Column (3) simply replaces investment with capital stock, while column (4) uses investment as an instrument for process innovation, but capital in the production function. Column (5) includes both investment and capital in both equations.

The results are somewhat encouraging: capital stock is clearly preferred in the production function. In fact, when it is included, investment enters only via its impact on process innovation. On the other hand, investment is a better predictor of process innovation, although capital still plays a role. However, recall that innovation is measured over the preceding 3 years, so that some of the investment associated with process innovation is likely to be already included in beginning of year capital. Our conclusion is that there is a strong association of process innovation with capital investment and that such process innovation has a large impact on productivity.

3.8 Comparison to Griffith et al. 2006

The results shown in the previous section can help in shedding some light on the R&D-innovation-productivity relationship in Italian firms. Interesting insights can be gained from the differential impact of R&D on process and product innovation, as well as their different impact on productivity. Nevertheless, at this point, it is worth asking a further question: is the R&D-innovation-productivity link different for Italian firms when they are compared to other European countries? In order to answer this question, we built a slightly different sample of firms from our data that removed firms with fewer than 20 employees and included firms with more than 250 employees.[13] Using this sample, we are able to compare our estimates to those for France, Germany, Spain and the UK (Griffith et al. 2006). Table 6 presents the results of this comparison.[14] The last two columns are for Italy, the column before the last being for the same period (1998–2000), and the last one for our overall sample for the three periods 1995–1997, 1998–2000 and 2001–2003 pooled together.

The Table shows that the results for Italy are roughly comparable with those for the other countries, but that the period (1998–2000) seems to be a bit of an outlier. We do not have an explanation for this fact other than to point out that this period corresponds to the introduction of the euro. We therefore focus on the results for the overall sample. R&D intensity is somewhat more strongly associated with process innovation than in the UK and much less strongly than in the other countries. Investment intensity is more strongly related to process innovation than in the other countries. Also noteworthy is that for Italy, the explanatory power of the innovations equations is considerably lower.

[12] The sample size in this table is 9,014, reduced from 9,674 in the main tables of the paper due to the absence of lagged capital (beginning of year capital) for some of the observations.

[13] The overlap of this sample with the sample used in the main body of the paper is 75%.

[14] For precise comparability with the earlier paper, in this table we estimated the process and product innovation equations using single probits rather than a bivariate probit. This is consistent, but not efficient, given the correlation between the two equations.

Table 6 Comparison with Griffith et al. (2006)

Period: 1998–2000	France	Germany	Spain	UK	Italy	Italy[a]
Number of observations	3,625	1,123	3,588	1,904	2,594	8,377
Process innovation equation						
R&D intensity[b]	0.303***	0.260***	0.281***	0.161***	0.146***	0.192***
Investment intensity[b]	0.023***	0.022***	0.029***	0.037***	0.054***	0.049***
Pseudo R^2	0.213	0.202	0.225	0.184	0.050	0.091
Product innovation equation						
R&D intensity[b]	0.440***	0.273***	0.296***	0.273***	0.192***	0.303***
Pseudo R^2	0.360	0.313	0.249	0.258	0.058	0.081
Labor productivity equation						
Investment intensity[b]	0.130***	0.109***	0.061***	0.059***	0.129	0.109***
Process innovation	0.069**	0.022	−0.038	0.029	−0.874	0.011
Product innovation	0.060***	−0.053	0.176***	0.055***	1.152	0.384
R^2	0.290	0.280	0.180	0.190	0.166	0.227

This table is based on tables in Griffith et al. 2006. Data are from the third Community Innovation Survey (CIS 3) for France, Germany, Spain and the UK. Results for Italy come from Tables 3, 4 and 5 of this paper

[a] This column shows data for all three periods in Italy (1995–1997, 1998–2000, 2001–2003)

[b] Units are logs of euros (2000) per employee

* Significant at 10%, ** significant at 5%, *** significant at 1%

In the productivity equation, only investment intensity enters, although product innovation has a large but insignificant impact, larger than that for any of the other countries. Together with the results for the innovation equations, this suggests that the variability in the R&D-innovation-productivity relationships is much greater for Italy than for the other countries. However, there is nothing obviously different about the relationship itself when compared to its peers in Europe, apart from the fact that R&D appears less closely linked to process innovation in Italian firms.

4 Conclusions and policy discussion

In this paper we have proposed and estimated a structural model that links R&D decisions, innovation outcomes and productivity at the firm level. Based upon a modified version of the model earlier developed by Crépon et al. (1998), we were able to take into account also those firms that do not do (or report) explicitly R&D. Innovation activity, especially among small firms, can operate along several dimensions besides formal R&D.

Although preliminary, our results indicate that firm size is negatively associated with the intensity of R&D, but positively with the likelihood of having product or process innovation. We have argued that these two findings are not inconsistent, given the nature of the variables. Having received a subsidy boosts R&D efforts—or just the likelihood of reporting, more in high-tech industries, even if the share of targeted firms is roughly the same in high- and low-tech industries (46% vs. 45%). Given firms' unwillingness to reveal more details about the subsidies received, we can only speculate about the possibility that high-tech firms are more likely to receive funding for innovation and R&D than low-tech firms. International (including European) competition fosters R&D intensity, especially in high-tech firms. We find that R&D has a strong and sizeable impact on firm's ability to produce process innovation and a somewhat higher impact on product innovation. Investment in new equipment and machinery matters more for process innovation than for product innovation.

While interpreting these results, one should keep in mind the dual nature of R&D. In fact, R&D investments contribute to developing the firm's ability to identify, assimilate and exploit knowledge from other firms and public research organizations (Cohen and Levinthal 1989). In other words, a minimum level of R&D activity is a necessary condition to benefit from spillovers and to appropriate public knowledge. On the other hand, more recent studies have suggested the emergence of a different knowledge paradigm, i.e., the one of innovation without research, particularly well suited for SMEs (Cowan and van de Paal 2000), based on "the recombination and re-use of known practices" (David and Foray 1995).

Finally, we find that product innovation has a positive impact on firms' labor productivity, but that process innovation has a larger effect via the associated investment. Moreover, larger and older firms seem to be, to a certain extent, less productive, *ceteris paribus*.

With respect to the broader questions that motivated this investigation, we note that in most respects Italian firms resemble those in other large European countries. However, they do somewhat less R&D, and their R&D is less tightly linked to process innovation, but they are no less innovative, at least according to their own reports. Surprisingly, the firms in our sample are more rather than less productive than firms in other countries. Like Italian industry as a whole, they experienced a negative labor productivity growth during the 2000–2003 period, but apparently with no consequences on innovation activity and its estimated impact on productivity. Thus, we do not find any strong evidence of innovation "underperformance," other than the observation that those firms in our sample that do R&D do somewhat less on average than firms in comparable European countries.

In general, "underinvestment" relative to others may be due to demand factors (perceived market size, consumer tastes, etc.) and supply factors (high costs of capital or other inputs, availability of inputs and the regulatory environment). Stepping outside traditional economic analysis, factors such as having goals other than profit maximization, limited information about opportunities, or even social and cultural norms can also influence investment in innovation. Choosing among these alternatives definitively is beyond the scope of this paper, but we can offer a few tentative thoughts.

There is limited evidence that lower rates of R&D investment in larger Italian firms are due to the fact that they face a higher cost of capital than other firms in continental Europe. In a comparative analysis, Hall and Oriani (2006) find high marginal stock market values for Italian R&D investment in large firms that do not have a majority shareholder, which suggests a high required rate of return and therefore a high cost of capital. However for the other firms (closely held), R&D is not valued at all, which carries the implication that investment in these firms may not be profit driven. These conclusions suggest that a "bank-centered" capital market system, such as the Italian one, with a shortage of specialized suppliers, like venture capitalists (Rajan and Zingales 2003), is less capable of valuing R&D projects (Hall 2002). Smaller firms and those that are family-controlled with a pyramidal structure, which are quite common in Italy, are likely to be affected by credit rationing problems and/or to have goals other than profit maximization. But this is to some extent speculative, and we hope to explore the question further in the future.

Acknowledgements We would like to thank the Mediocredito-Capitalia (now Unicredit) research department for having kindly supplied firm level data for this project. We thank also Susanto Basu, Ernie Berndt, Piergiuseppe Morone, Stéphane Robin, Mike Scherer, Enrico Santarelli, Alessandro Sembenelli, Marco Vivarelli and participants at the NBER Productivity Seminars, at the workshop "Drivers and Impacts of Corporate R&D in SMEs" held in Seville at IPTS. The views expressed by the authors do not necessarily reflect those of the Bank of Italy.

Appendix: variable definitions and supplementary tables

R&D engagement: dummy variable that takes value 1 if the firm has positive R&D expenditures over the 3 years of each wave of the survey.

R&D intensity: R&D expenditures per employee, in real terms and in logs.

Process innovation: dummy variable that takes value 1 if the firm declares to have introduced a process innovation during the 3 years of the survey.

Product innovation: dummy variable that takes value 1 if the firm declares to have introduced a product innovation during the 3 years of the survey.

Innovator: dummy variable that takes value 1 if the firm has process or product innovation.

Share of sales with new products: percentage of the sales in the last year of the survey coming from new or significantly improved products (in percentage).

Labor productivity: real sales per employee, in logs.

Investment intensity: investment in machinery per employee, in logs.

Public support: dummy variable that takes value 1 if the firm has received a subsidy during the 3 years of the survey.

Regional–national–European–international (non EU) competitors: dummy variables to indicate the location of the firm's competitors.

Large competitors: dummy variable that takes value 1 if the firm declares to have large firms as competitors.

Employees: number of employees, headcount.

Age: firm's age (in years).

Size classes: [11–20], [21–50], [51–250] employees.

Age classes: [<15], [15–25], [>25] years.

Industry dummies: a set of indicators for a two-digit industry classification.

Time dummies: a set of indicators for the year of the survey.

Wave dummies: a set of indicators for firm's presence or absence in the three waves of the survey.

High-tech firms: encompasses high and medium-high technology industries (chemicals; office accounting and computer machinery; radio, TV and telecommunication instruments; medical, precision and optical instruments; electrical machinery and apparatus, n.e.c.; machinery and equipment; railroad and transport equipment, n.e.c.).

Low-tech firms: encompasses low and medium-low technology industries (rubber and plastic products; coke, refined petroleum products; other non-metallic mineral products; basic metals and fabricated metal products; manufacturing, n.e.c.; wood, pulp and paper; food, beverages and tobacco products; textile, textile products, leather and footwear).

Capital stock: fixed capital stock, in real terms, computed by a perpetual inventory method with constant depreciation rate ($\delta = 0.05$). The starting value is the accounting value as reported in firm's balance sheets (see Tables 7, 8 9 and 10).

Table 7 A comparison of selected variables for France, Germany, Spain, the UK and Italy

Period: 1998–2000	France	Germany	Spain	UK	Italy	Italy[b]
Number of observations (firms)	3,625	1,123	3,588	1,904	2,594	8,377
Continuous R&D engagement (%)	35.0	39.5	20.9	26.7	49.8	48.9
R&D per employee (for R&D-doers, mean)[c]	6.9	5.2	4.3	3.6	2.9	2.4
Innovator (process and/or product, %)	52.9	65.8	51.2	41.5	54.7	66.9
Process innovation (%)	32.3	42.3	34.7	27.1	44.7	55.4
Product innovation (%)	44.6	54.7	33.6	28.6	33.3	39.9
Share of sales with new products for firms with product innovation (%)	16.5	29.5	32.7	30.8	32.2	22.5
Labor productivity (mean)[c]	165.3	145.6	137.7	143.4	173.8	187.1
Investment per employee (mean)[c]	6.0	8.3	8.3	6.3	8.0	7.9
Public support for innovation (%)						
Local	5.5	15.8	14.0	4.5		
National	15.4	21.2	12.5	3.6	49.9 a	50.6 a
EU	5.1	8.1	3.3	1.7		
Percentage of firm in size class (20–49)	30.4	28.8	47.8	38.6	60.6	44.9
Percentage of firm in size class (50–250)	39.6	42.8	37.5	39.3	27.8	36.7
Percentage of firm in size class (>250)	30.0	28.5	14.7	22.1	11.1	18.4

This table is a slightly modified version of Table 3 in Griffith et al. 2006. Data are from the third Community Innovation Survey (CIS 3) for France, Germany, Spain and the UK. Data for Italy are from the Mediocredito Surveys. Among the several variables included in the original table, we selected only those comparable to our data. Data are not population-weighted

[a] This figure encompasses all the subsidies, regardless of their source

[b] This column shows data for all three periods in Italy (1995–1997, 1998–2000, 2001–2003)

[c] Units are logs of euros (2000) per employee

Table 8 A non-parametric selectivity test

Dependent variable	Probability (R&D > 0)	R&D expenditure per employee
D (Large firms)	0.150***	0.305
	(0.030)	(0.436)
D (Regional)	−0.138*	−0.230
	(0.056)	(0.408)
D (National)	0.012	0.0879
	(0.051)	(0.085)
D (European)	0.339***	0.826
	(0.057)	(0.988)
D (International)	0.391***	0.927
	(0.060)	(1.142)
D (Public subsidies for innovation)[a]	0.324***	0.761
	(0.028)	(0.943)
Group	0.145***	0.339
	(0.037)	(0.423)
Size class (21–50 employees)	0.147***	0.200
	(0.035)	(0.431)
Size class (51–250 employees)	0.482***	0.759
	(0.040)	(1.402)
Age class (15–25 years)	0.022	0.0258
	(0.036)	(0.089)
Age class (>25 years)	0.064	0.0684
	(0.036)	(0.197)
Constant	−0.563***	499.4
	(0.163)	(424.583)
Predicted probability (R&D > 0)		157.1
		(130.890)
Inverse Mill's ratio		92.21
		(81.214)
Square predicted probability (R&D > 0)		−399.9
		(336.616)
Square inverse Mill's ratio		183.7
		(152.908)
Predicted probability (R&D > 0) * inverse Mill's ratio		499.4
		(424.583)
Industry, time and wave dummies	Yes	Yes
R^2 or pseudo R^2	0.114	0.143
Number of observations	9,674	9,674

Standard errors are robust and clustered at the firm level

From this probit model we computed, for each observation in the sample, the inverse Mills' ratio, the predicted probability of having positive R&D and their quadratic and interaction terms

[a] This figure encompasses all the subsidies, regardless of their source

* Significant at 10%, ** significant at 5%, *** significant at 1%

Table 9 Robustness check for step 2 and 3

	(1)	(2)	(3)	(4)
Step 2—Process innovation				
Predicted R&D intensity	0.483*** [0.193]	0.544*** [0.217]	0.476*** [0.190]	0.547*** [0.218]
	(0.045)	(0.045)	(0.045)	(0.045)
Investment intensity	0.125*** [0.050]	–	0.137*** [0.055]	–
	(0.011)		(0.011)	
Step 2—Product innovation				
Predicted R&D intensity	0.686*** [0.250]	0.677*** [0.247]	0.660*** [0.241]	0.691*** [0.252]
	(0.045)	(0.046)	(0.046)	(0.045)
Investment intensity	–	0.021* [0.008]	0.055*** [0.020]	–
		(0.011)	(0.011)	
Step 3—Productivity including investment in the equation				
Predicted process innovation	0.193	−0.395	0.010	−0.432
	(0.267)	(0.275)	(0.255)	(0.277)
Predicted product innovation	0.597***	0.554***	0.599***	0.538***
	(0.093)	(0.087)	(0.095)	(0.086)
Investment intensity	0.099***	0.099***	0.093***	0.105***
	(0.010)	(0.006)	(0.009)	(0.006)
Step 3—Productivity without investment in the equation				
Predicted process innovation	2.624***	−1.318***	2.286***	−0.171
	(0.146)	(0.279)	(0.168)	(0.280)
Predicted product innovation	0.961***	0.895***	1.133***	0.773***
	(0.083)	(0.087)	(0.079)	(0.087)

Coefficients, marginal effects for step 2 in square brackets and standard errors are shown

The standard errors are robust to heteroskedasticity and clustered at the firm level

Industry, wave and time dummies are included in all equations

Reference groups: D (provincial competitors); size class (11–50 employees); age class (<15 years)

Specifications (1)–(4) encompass alternative assumptions for investment, whether it is devoted to process or product innovation, neither or both

* Significant at 10%, ** significant at 5%, *** significant at 1%

Table 10 Robustness check using lagged capital and ML estimation (9,014 observations)

Method of estimation:	(1) With investment *Sequential*	(2) With investment *pooled ML*	(3) With capital *pooled ML*	(4) Investment in process, capital in productivity *pooled ML*	(5) With both *pooled ML*
Step 2—Process innovation					
Predicted R&D intensity	0.440***	0.400***	0.416***	0.399***	0.389***
	(0.048)	(0.074)	(0.078)	(0.073)	(0.075)
Log investment per employee	0.131***	0.142***		0.145***	0.120***
	(0.011)	(0.013)		(0.011)	(0.013)
Log capital stock per employee[a]			0.098***		0.041***
			(0.013)		(0.014)
Step 2—Product innovation					
Predicted R&D intensity	0.652***	0.656***	0.655***	0.658***	0.661***
	(0.047)	(0.094)	(0.094)	(0.093)	(0.095)
Step 3—Productivity equation					
Predicted process innovation without product innovation	0.517*	0.712*	0.902*	1.108***	0.855*
	(0.279)	(0.443)	(0.515)	(0.159)	(0.477)
Predicted product innovation	0.677***	1.081***	0.792**	0.881***	0.830**
	(0.108)	(0.310)	(0.337)	(0.314)	(0.370)
Log investment per employee	0.081***	0.072***			0.018
	(0.011)	(0.017)			(0.015)
Log capital stock per employee			0.108***	0.111***	0.101***
			(0.016)	(0.007)	(0.010)
Log likelihood	−27,119.9	−27,110.0	−26,979.0	−26,908.5	−26,901.3

The method of estimation is pooled maximum likelihood applied to the three steps, with the coefficient constraints imposed but without allowing for correlation among their disturbances. This method yields standard errors that account for the use of predicted variables in steps 2 and 3

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Marginal effects in square brackets

Industry, wave and time dummies are included in all equations

Reference groups: D (provincial competitors); size class (11–50 employees); age class (<15 years)

[a] Capital measured at the beginning of the period

* Significant at 10%, ** significant at 5%, *** significant at 1%

References

Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: An empirical analysis. *American Economic Review, 78*(4), 678–690.

Acs, Z. J., & Audretsch, D. B. (1990). *Innovation and small firms*. Cambridge, MA: MIT Press.

Amemiya, T. (1984). Tobit models: A survey. *Journal of Econometrics, 24*(1–2), 3–61.

Baldwin, J. R., Beckstead, D., & Caves, R. (2002). Changes in the diversification of Canadian manufacturing firms (1973–1997): A move to specialization. *Research Paper Series* 11F0019MIE2002179, Statistics Canada.

Baldwin, J. R., & Gu, W. (2003). Participation in export markets and productivity performance in Canadian manufacturing. *Canadian Journal of Economics, 36*(3), 634–657.

Benavente, J. M. (2006). The role of research and innovation in promoting productivity in Chile. *Economics of Innovation and New Technology, 15*(4/5), 301–315.

Blundell, R., Griffith, R., & Van Reenen, J. (1993). Knowledge stocks, persistent innovation and market dominance: Evidence from a panel of British manufacturing firms. Institute for Fiscal Studies, working paper N. W93/19.

Bönte, W. (2003). R&D and productivity: Internal vs. external R&D—evidence from West German manufacturing industries. *Economics of Innovation and New Technology, 12*, 343–360.

Brandolini, A., Casadio, P., Cipollone, P., Magnani, M., Rosolia, A., & Torrini, R. (2007). Employment growth in

Italy in the 1990s: Institutional arrangements and market forces. In: N. Acocella & R. Leoni (Eds.), *Social pacts, employment and growth*. Heidelberg: Physica-Verlag.

Cohen, W. M., & Klepper, S. (1996). A reprise of size and R&D. *The Economic Journal, 106*(437), 925–951.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal, 99*(397), 569–596.

Cowan, R., & van de Paal, G. (2000). *Innovation policy in the knowledge-based economy*. Brussels: European Commission DG-Enterprise.

Crépon, B., Duguet, E., & Mairesse, J. (1998). Research, innovation and productivity: An econometric analysis at the firm level. *Economics of Innovation and New Technology, 7*(2), 115–158.

Das, M., Newey, W. K., & Vella, F. (2003). Nonparametric estimation of sample selection models. *Review of Economic Studies, 70*(1), 33–58.

Daveri, F., & Jona-Lasinio, C. (2005). Italy's decline: Getting the facts right. *Giornale degli Economisti, 64*(4), 365–410.

David, P., & Foray, D. (1995). Accessing and expanding the science and technology knowledge base. *STI Review, 16*, 16–38.

European Commission. (2006). *European trend chart on innovation*. Country Report, Italy. Enterprise Directorate-General.

Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and productivity across four European countries. *Oxford Review of Economic Policy, 22*(4), 483–498.

Griliches, Z. (1995). R&D and productivity: Econometric Results and Measurement Issues. In P. Stoneman (Ed.), *Handbook of the economics of innovation and technological change* (pp. 52–89). Oxford: Blackwell.

Griliches, Z. (1998). *R&D and productivity: The econometric evidence*. Chicago: Chicago University Press.

Hall, B. H. (2002). The financing of Research and Development. *Oxford Review of Economic Policy, 18*(1), 35–51.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation and productivity: Evidence from Italian microdata. *Industrial and Corporate Change, 17*, 813–839.

Hall, B. H., & Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics, 65*(1), 263–293.

Hall, B. H., & Mairesse, J. (2006). Empirical studies of innovation in the knowledge-driven economy. *Economics of Innovation and New Technology, 15*(4/5), 289–299.

Hall, B. H., & Oriani, R. (2006). Does the market value R&D investment by European firms? Evidence from a panel of manufacturing firms in France, Germany, and Italy. *International Journal of Industrial Organization, 24*(5), 971–993.

Harhoff, D. (1998). R&D and productivity in German manufacturing firms. *Economics of Innovation and New Technology, 6*(1), 29–49.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153–161.

Heshmati, A., & Lööf, H. (2006). On the relation between innovation and performance: A sensitivity analysis. *Economics of Innovation and New Technology, 15*(4/5), 317–344.

Hoffman, K., Parejo, M., Bessant, J., & Perren, L. (1998). Small firms, R&D, technology and innovation in the UK: A literature review. *Technovation, 18*(1), 39–55.

Janz, N., Lööf, H., & Peters, A. (2004). Firm level innovation and productivity—is there a common story across countries? *Problems and Perspectives in Management, 2*, 1–22.

Jefferson, G. H., Huamao, B., Xiaojing, G., & Xiaoyun, Y. (2006). R&D performance in Chinese industry. *Economics of Innovation and New Technology, 15*(4/5), 345–366.

Kleinknecht, A. (1987). Measuring R&D in small firms: How much are we missing? *The Journal of Industrial Economics, 36*(2), 253–256.

Klette, T. J., & Johansen, F. (1996). Accumulation of R&D capital and dynamic firm performance: A not-so-fixed effect model. Discussion papers 184, Research Department of Statistics Norway.

Klette, T. J., & Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of Political Economy, 112*(5), 986–1018.

Klomp, L., & Van Leeuwen, G. (2001). Linking innovation and firm performance: A new approach. *International Journal of the Economics of Business, 8*(3), 343–364.

Lichtenberg, F. R., & Siegel, D. (1991). The impact of R&D investment on productivity: New evidence using linked R&D-LRD data. *Economic Inquiry, 29*(2), 203–228.

Lööf, H., & Heshmati, A. (2002). Knowledge capital and performance heterogeneity: A firm level innovation study. *International Journal of Production Economics, 76*(1), 61–85.

Lotti, F., & Santarelli, E. (2001). Linking knowledge to productivity: A Germany–Italy comparison using the CIS database. *Empirica, 28*, 293–317.

Mairesse, J., & Mohnen, P. (2005). The importance of R&D for innovation: A reassessment using French Survey Data. *The Journal of Technology Transfer, 30*(1–2), 183–197 (special issue in memory of Edwin Mansfield).

Mairesse, J., & Sassenou, M. (1991). R&D productivity: A survey of econometric studies at the firm level. NBER working paper no. 3666.

Mohnen, P., Mairesse, J., & Dagenais, M. (2006). Innovativity: A Comparison across seven European countries. *Economics of Innovation and New Technology, 15*(4/5), 391–413.

Pakes, A., & Griliches, Z. (1984). Patents and R&D at the firm level: A first look. In Z. Griliches (Ed.), *R&D, patents, and productivity* (pp. 55–71). Chicago: University of Chicago Press.

Parisi, M. L., Schiantarelli, F., & Sembenelli, A. (2006). Productivity innovation and R&D: Micro evidence for Italy. *European Economic Review, 50*, 2037–2061.

Pianta, M., & Vaona, A. (2007). Innovation and productivity in European industries. *Economics of Innovation and New Technology, 16*(7), 485–499.

Potters, L., Ortega-Argilés, R., & Vivarelli, M. (2008). R&D and productivity: Testing sectoral peculiarities using micro data. IZA discussion paper no. 3338.

Rajan, R. G., & Zingales, L. (2003). Banks and markets: The changing character of European finance. NBER working paper no. 9595.

Van Leeuwen, G., & Klomp, L. (2006). On the contribution of innovation to multi-factor productivity growth. *Economics of Innovation and New Technology, 15*(4/5), 367–390.

Vella, F. (1998). Estimating models with sample selection bias: A survey. *The Journal of Human Resources, 33*(1), 127–169.

Verspagen, B. (1995). R&D and productivity: A broad cross-section cross-country look. *Journal of Productivity Analysis, 6*, 117–135.