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Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms

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Both research and development (R&D) and information and communication technology (ICT) investment have been identified as sources of relative innovation underperformance in Europe vis-à-vis the USA. In this article, we investigate the R&D and ICT investment at the firm level in an effort to assess their relative importance and to what extent they are complements or substitutes. We use data on a large unbalanced panel data sample of Italian manufacturing firms constructed from four consecutive waves of a survey of manufacturing firms, to estimate a version of the CDM model of R&D, innovation, and productivity [Crépon–Duguet–Mairesse 1998. Research, innovation and productivity: An econometric analysis at the firm level. *Economics of Innovation and New Technology* 7, no. 2: 115–58] that has been modified to include ICT investment and R&D as the two main inputs into innovation and productivity. We find that R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation, and ICT investment being more important for productivity. For the median firm, rates of return to both investments are so high that they suggest considerably underinvestment in both these activities. We explore the possible complementarity between R&D and ICT in innovation and production, but find none, although we do find complementarity between R&D and worker skill in innovation.

Keywords: R&D; ICT; innovation; productivity; complementarity; Italy

JEL Classification: L60; O31; O33

1. Introduction

Both research and development (R&D) and information and communication technology (ICT) investments have been identified as areas of relative underperformance in Europe vis-à-vis the USA. For example, van Ark, Inklaar, and McGuckin (2003) concluded the following in their study of the reasons for lower productivity growth in Europe: 'The results

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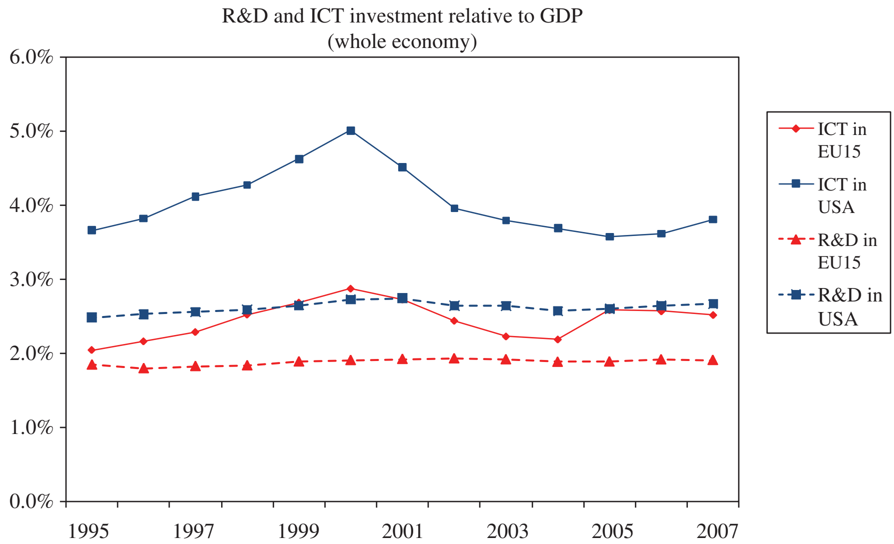

Figure 1. R&D and ICT investment relative to GDP (whole economy).

show that U.S. productivity has grown faster than in the EU because of a larger employment share in the ICT-producing sector and faster productivity growth in services industries that make intensive use of ICT'. Also see Mairesse and Kocoglu (2005) for a comparison of the contribution of ICT investment and R&D to growth in the USA and Europe. Moncada-Paternò-Castello et al. (2009), Hall and Mairesse (2009), and O'Sullivan (2006) all point to the differences in industrial structure, specifically the smaller ICT-producing sector as the main cause of lower R&D intensity in Europe.

It is also true that the ICT share of investment by firms in all sectors is lower in Europe than in the USA. Figure 1 shows the R&D investment–GDP and ICT investment–GDP shares for the EU15 and the USA over the 1995–2007 period. Both show a significant gap and the ICT gap is somewhat larger than that for R&D. Thus, not only is the ICT-producing sector smaller in Europe, but it is also true that less investment in ICT is taking place relative to GDP. So it is natural to ask whether ICT investment results in innovation and productivity growth in European firms, and how this kind of investment interacts with R&D investment. Do European firms invest less in ICT because the productivity of such investment is low or are there other causes for this low investment rate? Looking at ICT investment within Europe, as we do in Figure 2, we can see that the laggards in ICT as a share of all investment are Austria, Italy, Portugal, and Spain.[1] This is one of the reasons why this article directs its attention to data on Italian firms.

There is also considerable policy interest in the implications of these kinds of investment (R&D and ICT) for the skill composition of the workforce. One might expect that R&D would be targeted mainly at new and significantly improved product innovation (following the results of much earlier surveys, such as Mansfield 1968). In contrast, ICT investment has frequently been found to be accompanied by innovations in processing and the organization of work within the firm. To our knowledge, very few papers have investigated R&D and ICT investments jointly and tried to assess their relative importance and to what extent they are complements or substitutes. The few articles in the literature have produced conflicting results. For example, while Cerquera and Klein (2008) find that a more intense use of ICT brings about a reduction in R&D effort in German firms, Polder et al. (2009) find a

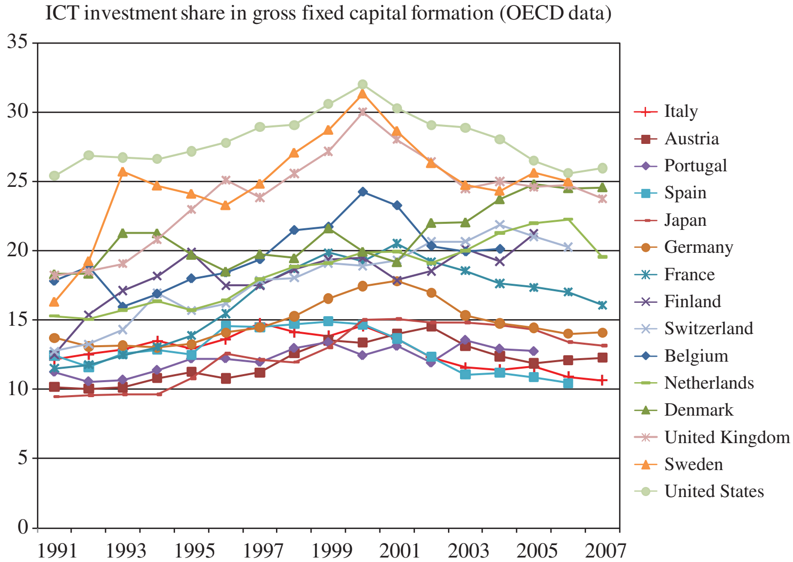

Figure 2. ICT investment share in gross fixed capital formation (OECD data).

complementarity effect of ICT with respect to innovation in the service sector only in the Netherlands, albeit one that is small in magnitude.

In this article, we use a version of the well-known Crépon–Duguet–Mairesse (CDM) model of R&D, innovation, and productivity (Crépon–Duguet–Mairesse 1998; Griffith et al. 2006) to go beyond prior work in this area. We treat ICT in parallel with R&D as an input to innovation rather than simply as an input of the production function. By doing this, we take into account the possible complementarities among different types of innovation activities. In addition, we add measures of organizational innovation to explore the interaction among all these factors. Our analysis examines the firm-level relationships between product, process and organizational innovation, labor and total productivity, and two of their major determinants, namely R&D and ICT, using data on firms from a single European country, Italy. The evidence is based on a large unbalanced panel data sample of Italian manufacturing firms in the 1995–2006 period, constructed from the four consecutive waves of the 'Survey on Manufacturing Firms' conducted by Unicredit.

Taking advantage of our previous work (Hall, Lotti, and Mairesse 2008, 2009), and as in Polder et al. (2009), we thus rely on an extension of a modified version of the CDM model that includes ICT investment together with R&D as two main inputs into innovation and productivity. This extension of the model specification leads to augmented difficulties in estimation owing to the increased number of equations with qualitative-dependent variables: we bypass some of these difficulties by estimating the different blocks of the model sequentially, while still correcting for endogeneity and selectivity in firm R&D investment.[2] We first consider a model of R&D investment (consisting of a probit for the presence of the investment and a regression that predicts its level). Next, we test different sets of (univariate and quadrivariate) probit equations for binary indicators of product, process, and organizational innovation with the levels of R&D and ICT investments as predictor variables. Finally, we estimate the productivity impacts of the different modes of innovation in a production function, controlling for physical capital.

The next section of the article reviews the micro-econometric evidence on the use of ICT to enhance the productivity of firms. This is followed by a presentation of our model, data, and the results of estimation. The final section offers some preliminary conclusions.

2. ICT and productivity: a micro perspective

The earliest studies on the link between ICT and productivity at the macro level were mainly aimed at understanding the so-called Solow paradox, that is, the fact that 'computers were visible everywhere except in the productivity statistics'.

In fact, measuring ICT correctly at the aggregate level is a non-trivial issue. The ideal measure capturing the economic contribution of capital inputs in a production theory context is the flow of capital services, but building this variable from raw data entails non-trivial assumptions regarding the measurement of the investment flows in the different assets and the aggregation over vintages of a given type of asset. Moreover, deflators must be based on hedonic techniques given the rapid technical change in this sector.

Availability of data at the firm level enables one to overcome some of the aforementioned issues and at the same time to account for heterogeneity. In fact, many studies find an impact on the productivity that is greater than that for ordinary non-ICT investment, measuring ICT with alternative proxies, like a measure of the stock of a firm's computer hardware at the establishment level (Brynjolfsson and Hitt 1995, 2000; Brynjolfsson and Yang 1998; Brynjolfsson, Hitt, and Yang 2002), ICT use at the firm level (number of PCs, the use of network, number of employees using ICT; Greenan and Mairesse 2000) and ICT investment expenditure. The latter measure is clearly desirable, as it provides a direct measure of investment outlay that can be easily used in a production function and we will rely on it in our empirical analysis. Also, when working with cross-section data, as we do here, such an investment measure is highly correlated with the corresponding capital stock measure at the firm level, and much easier to measure.

Even if based on different indicators, the relationship between ICT and productivity at the firm level is generally positive (Black and Lynch (2001) and Bresnahan, Brynjolfsson, and Hitt (2002) for the USA, Greenan, Topiol-Bensaid, and Mairesse (2001) for France, Bugamelli and Pagano (2004) and, more recently, Castiglione (2009) on Italy), but ICT alone is not enough to affect productivity. In fact, Black and Lynch (2001) and Bresnahan, Brynjolfsson, and Hitt (2002) focus on the interaction between ICT, human capital, and organizational innovation. Ignoring these complementarities may lead to overestimating the effect of ICT on productivity. In fact, development of ICT projects requires reorganization of the firm around the new technology, but reorganization needs time to be implemented and, more importantly, it implies costs, such as retraining of workers, consultants, and management time. See also Brynjolfsson, Hitt, and Yang (2002) on the firm valuation effects of information technology acquisition, which they show to be partly proxying for the costs of the organizational change that accompanies such acquisition.

Therefore, we treat ICT as an input, both of the production function and, more importantly, of the knowledge production function. In the first case, we reconcile with a more traditional view: ICT enables 'organizational' investments, mainly business processes and new work practices which, in turn, lead to cost reductions and improved output and, hence, productivity gains. In a less traditional view, ICT is an input for producing new goods and services (such as internet banking), new ways of doing business (B2B), and new ways of producing goods and services (integrated management). Consequently, in our modeling framework, we treat ICT as a pervasive input rather than an input of the production function only. By doing so, we take explicitly into account possible complementarities with innovation activity, mainly R&D but also organizational innovation.

We directly incorporate ICT expenditure into the 'CDM' framework which intends to shed some light in the black box on the innovation process at the firm level by linking in some details innovation inputs to innovation outputs and innovation outputs to productivity, and not only by considering a reduced form relation from innovation inputs to productivity. The CDM framework follows the logic of firms' decisions by distinguishing three types of equations (or groups of equations) for respectively investment in innovation inputs, the production of innovation outputs (or knowledge production function) and the traditional production function augmented to include innovation outputs as additional factors of productivity. We extend the CDM model to include an equation for ICT as an enabler of innovation and organizational innovation as an indicator of innovation output, as in Polder et al. (2009). Using data from different sources (mainly surveys) at the Statistics Netherlands on firms belonging to the manufacturing and services industries, Polder et al. find that ICT is an important driver of innovation. While doing more R&D has a positive effect on product innovation in manufacturing only, they positive effects of product and process innovation when combined with organizational innovation in both sectors.

3. The extended CDM framework

The framework thus encompasses three groups of relations as shown in Figure 3. The first consists of the decision whether to invest in R&D or not and how much to invest.[3] The second consists of a set of binary innovation outcomes during the previous three years: introduction of a new or significantly improved process, introduction of a new or significantly improved product, organizational change associated with process innovation, or organizational change associated with product innovation. These outcomes are presumed to be driven by the investment decisions of the firms with respect to R&D and physical capital. The element of novelty is the inclusion of ICT expenditure at this stage to explain innovation activity. The final equation is a conventional labor productivity regression that includes the innovation outcomes as well. All of the equations in the model are projected on a list of 'exogenous' variables that include a quadratic in the log of firm size, a quadratic in the log of firm age, year dummies, survey wave dummies, 20 two-digit industry dummies, and 20 regional dummies. The survey wave dummies are a set of indicators for the firm's presence or absence in the four waves of the survey.[4] The left-out categories are the 1998 year, the machinery industry, the Lombardy region (including Milan), and the first wave pattern.

To summarize, productivity is assumed to depend on innovation, and innovation to depend on investment choices. Of necessity, our estimation is cross-sectional only, for two reasons: first, we have few firms cases with more than one year (the average number of observations per firm is 1.4). Second, the timing of the questions of the survey is such that we cannot really assume a direct causal relationship between investment and innovation, since both are measured over the preceding three years in the questionnaire. Therefore, the results that we report should be viewed as associations rather than as causal relationships. This use of a cross-sectional approach also means that the use of investment flows rather than stocks in the innovation equations is mostly inconsequential. The following sections discuss the models estimated in more detail.

3.1. The R&D decision

In this first stage, as in the standard CDM model, we treat the decision to invest in R&D. A firm must decide whether to do R&D or not, then, given that the firm chooses to do R&D, it

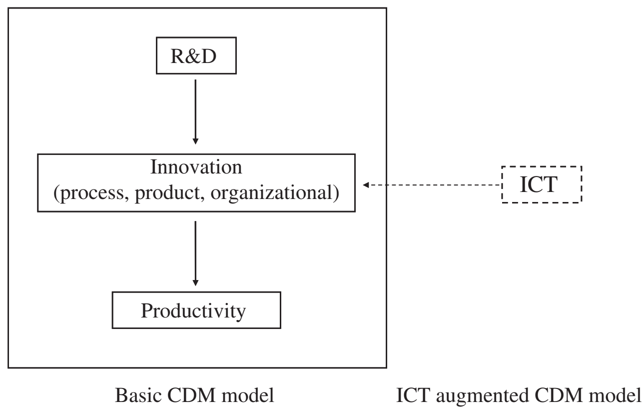

Figure 3. Basic and augmented CDM model.

must choose the investment intensity. This statement of the problem can be modeled with a standard sample selection model. We use X to denote R&D investment, and define the model as follows:

$$DX_i = \begin{cases} 1 & \text{if} \quad DX_i^* = w_i\alpha + \varepsilon_i > \bar{c}, \\ 0 & \text{if} \quad DX_i^* = w_i\alpha + \varepsilon_i \le \bar{c}, \end{cases} \tag{1}$$

where DX_i is an (observable) indicator function that takes the value 1 if firm i has (or reports) positive expenditures on X, DX_i^* is a latent indicator variable such that firm i decides to perform (or to report) expenditures if it is above a given threshold $\bar{c}$, w_i is a set of explanatory variables affecting the decision, and is the error term. For those firms doing R&D, we observe the intensity of resources devoted to these activities:

$$X_i = \begin{cases} X_i^* = z_i\beta + e_i & \text{if} \quad DX_i = 1, \\ 0 & \text{if} \quad DX_i + 0, \end{cases} \tag{2}$$

where X_i^* is the unobserved latent variable corresponding to the firm's investment, and z_i is a set of determinants of the expenditure intensity. We measure expenditure intensity as the logarithm of R&D spending per employee. Assuming that the error terms in Equations (1) and (2) are bivariate normal with zero mean and covariance matrix given by

$$\begin{pmatrix} 1 & \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix}. \tag{3}$$

The system of Equations (1) and (2) can be estimated by the 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 for R&D, we performed a semi-parametric test for the presence of selection bias (see Das, Newey, and Vella (2003) and Vella (1998) for a survey). Results are in Table A3 in the appendix. Unlike the case in Hall, Lotti, and Mairesse (2009), who used only small- and medium-sized firms, we found significant bias in the R&D equation from selection, so we included the selection model in our estimation strategy.

3.2. Innovation outcomes

In the second step, we estimate a knowledge production function but, unlike the original CDM model, we add ICT investment as a possible determinant of innovation. In order to account for that part of innovation activity that has not been formalized, we do not restrict estimation to R&D or ICT performing firms only. This is likely to be especially important for small and medium-sized enterprises, which represent nearly 90% of our sample. The outcomes of the knowledge production function are four types of innovations: product, process, and organizational innovations associated with either of these:[5]

$$\mathrm{INNO}_i^j = \gamma_j \mathrm{RD}_i^* + \gamma_j^{\mathrm{ICT}} \mathrm{ICT}_i + \gamma_j^I I_i + x_i \delta_j + u_{ji} \quad j = 1, \ldots, 4, \tag{4}$$

where RD_i^* is the latent R&D effort, which is proxied by the predicted value of R&D from the model in the first step, ICT_i is ICT investment intensity, I_i is physical investment intensity[6] (other than ICT), and the error terms $\{u_j\}$ are distributed normally with covariance matrix Σ.

We measure ICT and ordinary investment intensities as the log of annual expenditure per employee. We argue that including the predicted R&D intensity in the regression accounts for the fact that all firms may have some kind of innovative effort, but only some of them report it (Griffith et al. 2006). Moreover, using the predicted value instead of the realized value is a sensible way to instrument the innovative effort in the knowledge production function in order to deal with simultaneity problem between R&D and the expectation of innovative success. However, given the fact that the model is estimated in sequential stages, conventional standard error estimates will be biased and we present standard errors computed via a panel bootstrap. In general, using a bootstrap makes relatively little difference to the standard errors, except those for the innovation probability in the productivity equation.

We also explored the use of our measures of skill in predicting innovative activity. We have two types of measures available: the number of employees with diploma *superiore* degrees (high school) and laurea degrees (college), and the number of employees that are executives or white-collar workers. It turns out that the degree shares were much weaker predictors, so we chose to focus on the share of executives and white-collar workers as a proxy for the employee skills. There are several reasons why the degree shares are not good predictors: first of all there are substantially more missing values than for the other skill indicator. Nonetheless, looking at the raw numbers, only 4.7% of the employees in our sample have a college degree: too few for a robust identification. Second, it is more plausible that the respondent has a clear idea about the partitioning of the labor force in terms of share of executives and white collar rather than for its level of education. Third, educational and skill mismatches are a very common phenomenon, especially in smaller firms (Ferrante 2010).

Equation (4) is estimated as a quadrivariate probit model using the Geweke–Hajivassiliou–Keane algorithm (Cappellari and Jenkins 2003, 2006; Greene 2003), assuming that the firm characteristics which affect the various kinds of innovation are the same, although of course their impact may differ. We also estimate a univariate, and various bivariate and trivariate probit versions of the model, finally concluding that the various types of innovation and their predictors are so correlated that it is not possible to extract more than one dimension of innovation from them.

3.3. The productivity equation

In the third and final step of the model, production is modeled using a simple Cobb–Douglas technology with labor, capital, and knowledge inputs:

$$y_i = \pi_1 k_i + \mathrm{INNO}_i^* \pi_2 + Z_i \psi + v_i, \tag{5}$$

where y is the labor productivity (sales per employee, in logs), k is the log of capital per worker, INNO* is the predicted probability of innovation from the second step, and the Z are the controls included in all equations. Note that Z includes the log of employment (size), so that this production equation does not impose constant returns to scale.

We tried to include in the productivity equation alternative combinations of the predicted probabilities of process, product, and organizational innovations, but the high levels of correlation between them prevented us from obtaining stable results. Therefore, in line with the results from Table 4, we decided to simply include the probability of any kind of innovation instead.

4. Data and descriptive statistics

We use firm-level data from the 7th, 8th, 9th, and 10th waves of the 'Survey on Manufacturing Firms' conducted by Unicredit (an Italian commercial bank, formerly known as Medicredito-Capitalia). These four surveys were carried out in 1998, 2001, 2004, and 2007, respectively, using questionnaires administered to a representative sample of Italian manufacturing firms. Each survey covered the three years immediately prior (1995–1997, 1998–2000, 2001–2003, and 2004–2006) and although the survey questionnaires were not identical in all four of the surveys, they were very similar in the sections used in this work. All firms with more than 500 employees were included in the surveys, whereas smaller firms were selected using a sampling design stratified by geographical area, industry, and

Table 1. Descriptive statistics, unbalanced sample.

Period: 1995–2006			
Number of observations (firms)	14,294 (9850)	Firms with large firms as competitors	39.1%
Number of employees (mean/median)	114/35	Firms with regional competitors	16.1%
Age (mean/median)	27/22.5	Firms with national competitors	41.9%
Firms with non-ICT investment	86.7%	Firms with EU competitors	17.4%
Firms with R&D	34.3%	Firms with international competitors	14.0%
Firms with ICT	68.3%	Firms within a group	24.7%
Share of executives in employees (mean/median)	1.8%/0.0%	Firms subsidies' recipients	37.2%
Share of white-collar workers in employees (mean/median)	26.2%/21.7%	Firms with product innovation	38.9%
Non-ICT investment intensity for firms that invest[a] (mean/median)	8.67/4.55	Firms with process innovation	50.9%
R&D intensity for R&D-doers[a] (mean/median)	3.79/1.66	Firms with both product and process innovation	26.9%
ICT intensity for ICT investors[a] (mean/median)	0.79/0.34	Firms with organizational innovation for product innovation	15.0%
Average capital intensity[a] (mean/median)	52.0/25.8	Firms with organizational innovation for process innovation	24.0%
Labor productivity[a] (mean/median)	219.5/157.8	Firms with high skill intensity	39.0%

[a]Units are real thousands of euros (base year = 2000) per employee.

Table 2. Innovation relationships across firms.

		Investing in ICT				
		No	Yes	Total		
Doing R&D	No	24.8%	40.9%	65.7%		
	Yes	6.9%	27.4%	34.3%		
	Total	31.7%	68.3%			
		Product innovation			Organizational change for process innovation	
		No	Yes		No	Yes
Process innovation	No	37.1%	12.0%	No	44.7%	4.4%
	Yes	24.0%	26.9%	Yes	31.3%	19.6%
Organizational change for product innovation	No	59.1%	25.9%	No	71.2%	13.8%
	Yes	2.0%	13.0%	Yes	4.8%	10.2%
Patterns of innovation						
Innovation dummy patterns	Obs	Share	Cum share		R&D-doers	ICT-investors
None	4683	32.8%	32.8%		13.8%	27.7%
Process only	2199	15.4%	48.1%		12.1%	15.5%
Product and process	2087	14.6%	62.7%		20.1%	14.6%
All (prod/proc/org)	1755	12.3%	75.0%		22.1%	15.3%
Process and organizational	1234	8.6%	83.7%		9.7%	10.3%
Product only	1212	8.5%	92.1%		12.0%	7.7%
Organizational only	624	4.4%	96.5%		4.3%	4.6%
Product and organizational	500	3.5%	100.0%		5.8%	4.2%
Total	14,294				34.2%	64.1%
Any product innovation	5554	38.9%			60.0%	41.8%
Any process innovation	7275	50.9%			64.1%	55.7%
Any organizational change	4113	28.8%			42.0%	34.4%

firm size. We merged the data from these four surveys, excluding firms with incomplete information or with extreme observations for the variables of interest.[7]

Our final sample is an unbalanced panel of 14,294 observations on 9850 firms, of which only 96 are present in all four waves. Table 1 contains some descriptive statistics for the unbalanced panel. Not surprisingly, the firm size distribution is skewed to the right, with an average of 114 employees, but with a median of 35 only. In our sample, two-thirds of the firms engage in some sort of innovation activity, but only 34% invest in R&D, with an average of 3800 euros per employee. While nearly 70% of the firms in the sample invest in ICT, the intensity with which they invest is much lower when compared with R&D, less than one thousand euros per employee. Roughly 20% of the employees at the median firm are white-collar workers, and although the average number of ‘executives’ is 1.8%, the median firm has none, which may reflect some errors in reporting. We use the sum of white-collar workers and executives as a proxy for skill in the regressions.

Turning to the variables, we will use to determine the R&D investment choice, 42% of the firms in the sample report that they have national competitors, while 17% and 14% have European and international competitors, respectively. A quarter of the firms belong to an industrial group. Interestingly, 42% of the firms in our sample received a subsidy of some kind (mainly for investment and R&D; we do not have more detailed information on the subsidies received). Only one-third of the sample consists of firms in high-tech industries, reflecting the traditional sector orientation of Italian industry.

In Table 2, we look at some of the innovation indicators more closely. A firm that invests in R&D is also slightly more likely to invest in ICT (compare 34% $*$ 68% $=$ 23–27%). For 27% of the firms, product and process innovations go together, while 24% are only process innovators. Only 30% of the firms report that they have undertaken organizational change associated with innovation; not surprisingly organizational change associated with either product or process innovation is more likely to accompany the corresponding type of innovation.

In the last panel of Table 2, we show the distribution of the various combinations of innovation activities: product, process, and organizational. There are $2^3 = 8$ possible combinations, but only four account for three quarters of the observations: no innovation (33%), only process innovation (15%), product and process together (15%), and all together (12%). In general, as we saw above, process innovation is more likely than product innovation for these firms, and either one more likely than organizational innovation. The final two columns in the bottom panel of Table 2 also show that there is some association between the various forms of innovation and both doing R&D and investing in ICT, although the association is stronger for R&D.

5. Results and discussion

5.1. R&D, ICT, and investment equations

To test for selection in R&D reporting, we first estimated a probit model in which the presence of positive R&D expenditures is regressed on a set of firm characteristics: firm size and its square, firm age and its square, a set of dummies indicating competitors' size and location, dummy variables indicating (i) whether the firm received government subsidies, and (ii) whether the firm belongs to an industrial group, along with industry, region, time, and wave dummies; the results are reported in Table A3 in the appendix. From this estimate, for each firm we recover the predicted probability of having R&D and the corresponding Mills' ratio. Then we estimate a simple linear (ordinary least squares (OLS)) for R&D intensity, adding to this equation the predicted probabilities from the R&D decision equation, Mills' ratio, their squares, and interaction terms. The presence of selectivity bias is then tested for by looking at the significance of those 'probability terms'.[8] The probability terms were jointly significant, with a $\chi^2(5) = 34.1$. We, therefore, concluded that selection bias was present and estimated the full two equation model by the maximum likelihood (the final two columns of Table A3). The results confirmed the presence of selection, with a highly significant correlation coefficient of almost 0.4. The interpretation of this result is that if we observe R&D for a firm for whom R&D was not expected, its R&D intensity will be relatively high given its characteristics. Conversely, if we fail to observe R&D, its R&D intensity is likely to have been low conditional on its characteristics.

Turning to the R&D intensity equation itself, we first observe that selection appears to have biased the coefficients toward zero in general, but did not have much effect on their significance (compare columns 2 and 4 of Table A3).[9] R&D intensity falls with size, reaching its minimum at about 380 employees and then rising again. It also falls with age, but this is barely significant. Firms facing European or other international competitors have much higher R&D intensities (by 20% or 30%), as do firms that are members of a group or who receive subsidies of some kind. These last two results suggest that financial frictions may be important for these firms.

For comparison to the R&D equation, we also estimated equations for ICT and non-ICT physical investment using OLS. Table 3 presents the results, along with our chosen specification for R&D investment. We do not expect that reporting bias or selection is as an

Table 3. R&D, ICT, and non-ICT investment per employee.

Dependent variable	Sample selection log R&D per employee	OLS log ICT per employee	OLS log investment per employee
Log employment	−0.242***	−0.126***	−0.050***
	(0.029)	(0.019)	(0.017)
Log employment squared	0.060***	0.045***	0.037***
	(0.012)	(0.009)	(0.007)
Log age	−0.049	0.031	−0.025
	(0.030)	(0.021)	(0.020)
Log age squared	0.011	0.007	0.009
	(0.029)	(0.020)	(0.019)
D (large firm competitors)	0.044	0.014	0.024
	(0.039)	(0.027)	(0.026)
D (regional competitors)	−0.107	−0.080	0.028
	(0.082)	(0.057)	(0.049)
D (national competitors)	−0.081	−0.007	−0.018
	(0.072)	(0.050)	(0.044)
D (European competitors)	0.225***	0.067	0.029
	(0.079)	(0.056)	(0.049)
D (international competitors)	0.329***	0.086	0.017
	(0.082)	(0.058)	(0.051)
D (received subsidies)	0.398***	0.089***	0.451***
	(0.043)	(0.028)	(0.026)
D (member of a group)	0.241***	0.239***	0.092***
	(0.047)	(0.035)	(0.032)
Employees at minimum	350	190	90
Chi-squared or F-test for competitor vars[a]	80.1***	3.3***	0.8
Chi-squared or F-test for industry dummies	277.7***	7.3***	31.7***
Chi-squared or F-test for regional dummies	68.7***	3.6***	1.7**
Chi-squared or F-test for time dummies	224.0***	15.0***	40.0***
Chi-squared or F-test for wave dummies	18.2	4.8***	3.9***
Standard error	1.278 (0.022)	1.237	1.283
R-squared	0.175	0.059	0.100
Number of observations	14,294 (4896 = 1)	9678	12,034

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern. [a]The first column shows a chi-squared test, and the others show F-tests.
**Significant at 5%.
***Significant at 1%.

important an issue for these kinds of investment, both because they are more easily tracked, and also because they do not exhibit the same magnitude of threshold effects arising from intertemporal non-separability and sunk costs that cannot be recaptured.[10] In general, we find that these kinds of investment are somewhat harder to predict than R&D. Like R&D, ICT and non-ICT intensities fall with size, but reach a minimum at smaller sizes of 100–200 employees and then increase again. The nature of competition does not appear to have much impact, but group membership and subsidies do. Being a member of a group boosts ICT investment by 25% and receiving subsidies (which are often investment subsidies) increases non-ICT investment by 40%. Interestingly, there is regional variation in R&D and ICT investments, but not in ordinary investment.

Summarizing these results, we conclude that European or international competition is only associated with higher R&D intensity, and not with higher tangible investment intensity. Financial constraints to R&D and ordinary investments are more likely to be mitigated by subsidies (which directly target these forms of investment), whereas ICT investment is more likely to be encouraged by group membership, probably because the costs are partly spread across the group, and also because the decision to install communication networks and computerize various functions may be a group decision.

Based on the results of this exploration of selection issues in the reporting of the three types of investment, in Section 5.2, we will use the predicted values of R&D intensity (the expectation of R&D intensity conditional on the other firm characteristics) and the reported values of ICT and non-ICT investment intensity to explain the propensity for different kinds of innovation. This approach is justified both by the evidence that there is reporting bias in R&D, but not in the other kinds of investment and by the observation that R&D is more difficult to measure, especially in smaller firms, because it occurs as a by-product of other activities and may not be separately tracked.

5.2. The innovation equations

Table A4 in the appendix presents the results of estimating a quadrivariate probit model for the four types of innovation as a function of predicted R&D investment, ICT, and non-ICT realized investments, and the size, age, and dummy variables. All four innovation variables have similar relationships to the size and R&D intensity of the firm, with the probability of innovation peaking somewhere between 500 and 1000 employees, and increasing strongly with R&D intensity. ICT investment intensity is associated with product and organizational innovations, but not with process innovation, although not having any ICT investment is strongly negative for process innovation. Older firms are more likely to be product-innovate, but the age of the firm is not associated strongly with other types of innovation. Finally, the residual correlation of the innovation variables after controlling for these factors is much higher than the raw correlations (see Table A5), suggesting that the firms have a strong idiosyncratic tendency toward innovation.

The model estimated in Table 4 can be used to generate the predicted probabilities of the $16 = 2^4$ possible combinations of types of innovation, all of which exist in our data. Unfortunately, we encountered considerable difficulty when we attempted to include these predicted values in the labor productivity equation, in the form of coefficient instability due to multicollinearity of the various predicted values. The upper panel of Table A5 in the appendix shows the correlation between the actual four types of innovation dummies; as expected, organizational innovation related to process or product innovation is highly correlated with the corresponding innovation type. The middle panel shows the correlations between the predicted innovation dummies, computed from the estimates of the quadrivariate probit model for innovation shown in Table A4. As one can observe, correlations are nearly doubled with respect to the actual values, ranging from 0.25 to 0.86. For this reason, the estimates were also quite sensitive to the inclusion and exclusion of other right-hand side variables, and to the exact form of the innovation equation. It appears that having only dummy variables for four different types of innovation is simply not enough information to measure the complex innovation profile of individual firms. Because we observe all 16 possible combinations in fairly sizable numbers in the data, the problem is not merely that some types of innovation are always accompanied by others, but more one of the substantial measurement error introduced when translating innovative activity into a simple, dichotomous 'yes or no' question.

To mitigate this problem and to attempt to obtain more stable results for the productivity equation, we considered collapsing the innovation indicators in all possible ways to make 3, 2, or 1 indicators, and then estimated the appropriate trivariate, bivariate, or univariate probit

Table 4. Probability of innovating.

Dependent variable	(1) Any innovation Coeff (s.e.)[a]	(1) Any innovation Marginal	(2) Any innovation Coeff (s.e.)[a]	(2) Any innovation Marginal
Predicted R&D intensity (in logs)	0.611*** (0.046, 0.053)	0.199	0.538*** (0.052, 0.058)	0.189
Share of executives and white-collar workers			0.118* (0.067, 0.063)	0.041
Interaction of predicted R&D and skilled share			0.221** (0.087, 0.094)	0.078
ICT investment per employee (in logs)	0.025** (0.012, 0.012)	0.015	0.022* (0.012, 0.012)	0.008
D (no ICT investment)	−0.374*** (0.029, 0.028)	−0.128	−0.370*** (0.029, 0.028)	−0.134
Investment per employee (in logs)	0.105*** (0.010, 0.009)	0.023	0.106*** (0.010, 0.009)	0.037
D (no investment)	−0.176*** (0.037, 0.032)	−0.097	−0.178*** (0.037, 0.032)	−0.065
Log employment	0.299*** (0.017, 0.028)	0.095	0.304*** (0.017, 0.028)	0.107
Log employment squared	−0.067*** (0.008, 0.012)	−0.021	−0.069*** (0.007, 0.012)	−0.024
Log age	0.031 (0.019, 0.022)	0.010	0.031* (0.019, 0.022)	0.011
Log age squared	−0.009 (0.018, 0.023)	−0.003	−0.008 (0.018, 0.023)	−0.003
Employees at maximum (s.e.)	438 (87)***		425 (85)***	
Number of observations	14,294		14,294	
Pseudo R-squared	0.101		0.102	
Log likelihood	−8126.6		−8118.1	
Bootstrap replications	100		100	

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern. A dummy for missing skill variables and its interaction with R&D intensity are included in column (2).
[a]The second s.e. in this column is a bootstrap estimate based on the R&D equations, with the number of replications given.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

model on the resulting data (results are not shown for the sake of clarity). We looked at the explanatory power of each model used by computing twice the log of the likelihood ratio for the fitted model versus a baseline multinomial model where the theoretical probability of each innovation combination is equal to the actual probability. These chi-squared measures capture the degree to which the fit of the model is improved by including the 64 regressors (size, age, R&D, ICT, investment along with year, wave, region, and sector dummies) in each probability equation.

Using the criterion of highest chi-squared improvement per coefficient, the most preferred specification turned out to be the simplest, where innovation is defined as simply any one or more of process, product, or organizational innovation associated with process or product, and the next most preferred combines the organizational innovation variables with the corresponding process and product variables. Our conclusion is that the answers to the four different innovation questions do not really provide information on four completely different activities, but rather on aspects of one or two kinds of innovative activity. That is, being innovative in the sense of introducing something new to the market or firm practice manifests itself in several directions at once, but the yes/no answer to the various ways the question is asked are sufficiently noisy to obscure this fact. Moreover, it is very likely that firms that introduce one type of innovation would naturally develop others to pursue efficiency in the production, whether or not they report them. To explore this issue, we will perform possible complementarity tests between the different kinds of innovation in a subsequent section of the paper.

Table 4 shows the results for two versions of the innovation probability equation, where innovation is defined as at least one of the process, product, and organizational innovations. The first equation shows that the most powerful predictor of innovation is the firm's R&D intensity, with a doubling of (predicted) R&D intensity leading to an increase in the probability of some kind of innovation equal to 20%. The other types of investment have much weaker impacts. The likelihood that a firm has at least one innovation increases strongly with firm size, reaching a maximum at about 400 employees. In this table, we also show standard errors obtained via 100 replications of a panel bootstrap on the R&D model and the innovation equation. They are roughly the same as the heteroskedastic-consistent standard errors computed by clustering on the firm, sometimes smaller and sometimes larger, so we conclude that estimating the model sequentially has not introduced much bias in the standard error estimates.

In the second column of Table 4, we show the results of predicting innovation when we add a skill variable (the share of executives and white-collar workers in the firm's employment) and its interaction with predicted R&D intensity. The other coefficients in the equation are largely unchanged by the addition of these variables, with the obvious exception of that for R&D intensity. The interaction term is quite significant and implies that a one standard deviation increase in the skilled share at the mean R&D intensity is associated with an increase in innovation probability of 4.4%. We also investigated the interaction of skills with ICT, finding no effect on innovation. So we conclude that the share of white-collar workers is complementary with R&D but not with ICT in innovating.

5.3. The labor productivity equation

In the last part of the analysis, we look at the productivity impacts of innovation activities. Table 5 shows estimates of Equation (5) with and without measures of R&D and ICT investments, and for two alternative indicators of innovation activities: the predicted probabilities of any innovation computed from the estimates in columns (1) and (2) of Table 4. Conventional variables (capital, employment, and the firm's age) are included in each specification and their estimates are usually not very affected by the inclusion of the innovation variables.

There are two sets of three estimates each, first for the probability of innovation predicted by R&D, ICT, and investment, and the second where the skill share of employment and its interaction with R&D have been added to the innovation prediction equation. In regressions not reported, we found that the dummy variable for the actual report by the firm of any kind of innovative activity would suggest that innovation has no effect on productivity, even in the absence of R&D or ICT investment. However, when we proxy innovation with the predicted probability of any innovation conditional on R&D, ICT, and the other firm characteristics included in Table 4, we find a positive effect: doing any kind of innovation increases productivity by 28% (column 1). Using the predicted probability instead of the actual presence/absence of innovation is more appropriate to account for possible endogeneity issues concerning knowledge inputs. In effect, we have instrumented the same

Table 5. Labor productivity equation.

Dependent variable	Labor productivity = Log(net sales per employee)					
	Probability predicted by Table 4(1)			Probability predicted by Table 4(2)		
Predicted probability of any innovation	0.275***	0.111	−0.310***	0.372***	0.285***	0.055
	(0.057)	(0.073, 0.104)[a]	(0.102, 0.109)[a]	(0.057)	(0.074)	(0.101, 0.108)[a]
Predicted R&D intensity (in logs)			0.166***			0.095***
			(0.028, 0.038)			(0.027, 0.039)
ICT investment per employee (in logs)		0.092***	0.098***		0.090***	0.093***
		(0.006, 0.005)	(0.006, 0.006)		(0.006)	(0.006, 0.005)
D (no ICT investment)		−0.097***	−0.152***		−0.070***	−0.101***
		(0.018, 0.020)	(0.020, 0.021)		(0.018)	(0.020, 0.021)
Log (capital per employee)	0.150***	0.140***	0.147***	0.146***	0.134***	0.138***
	(0.006)	(0.006, 0.008)	(0.006, 0.007)	(0.006)	(0.006)	(0.006, 0.007)
Log employment	−0.109***	−0.089***	−0.036***	−0.116***	−0.101***	−0.071***
	(0.010)	(0.010, 0.009)	(0.013, 0.013)	(0.010)	(0.010)	(0.013, 0.013)
Log employment squared	0.043***	0.038***	0.023***	0.044***	0.040***	0.031***
	(0.004)	(0.004, 0.004)	(0.005, 0.004)	(0.004)	(0.004)	(0.005, 0.004)
Log age	−0.028***	−0.029***	−0.021**	−0.028***	−0.029***	−0.024**
	(0.010)	(0.010, 0.010)	(0.010, 0.011)	(0.010)	(0.010)	(0.010, 0.011)
Log age squared	−0.005	−0.006	−0.008	−0.005	−0.006	−0.007
	(0.009)	(0.009, 0.009)	(0.009, 0.009)	(0.009)	(0.009)	(0.009, 0.009)
Employees at minimum (s.e.)	167	119	103	176	166	148
	(15)***	(14)***	(17)***	(15)***	(15)***	(17)***
Standard error	0.606	0.599	0.598	0.605	0.599	0.598
R-squared	0.238	0.256	0.257	0.239	0.256	0.257
Number of observations	14,294	14,294	14,294	14,294	14,294	14,294
Bootstrap replications		25	100			100

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D*(provincial competitors), Lombardia, year 1997, first wave pattern. [a]The second s.e. in this column is a panel bootstrap s.e. based on the R&D and innovation equations with the number of replications given.

**Significant at 5%.

***Significant at 1%.

poorly measure innovation dummy using inputs to innovation (R&D and ICT investment) and other firm characteristics.

Nevertheless, when we include R&D and/or ICT investment in the productivity equation (columns 2 and 3), the predicted probability of innovation activity loses (almost) all its significance. The ICT investment per employee appears to be a much better predictor of productivity gains than the probability of innovation predicted by ICT and R&D investments. When we include both predicted R&D and ICT investments, the innovation coefficient becomes negative, probably because of collinearity between innovation that is predicted using predicted R&D and predicted R&D by itself (net of the other variables in the regression). The interesting result is that when we use the skill variable to help predict innovation (columns 4–6), the collinearity problem is mitigated, and we find that the innovative activity helps to explain productivity, unless we also include the predicted R&D variable.

Columns 2, 3, and 6 of Table 5 also show panel bootstrap standard errors, computed by estimating the entire system (R&D selection and regression, the innovation probit, and the labor productivity equation) on samples drawn from our data.[11] This approach takes account of the predicted nature of R&D and the probability of innovation, but as can be seen in the table, the bootstrap standard errors are roughly the same as those computed in the conventional way allowing for heteroskedasticity and firm-level random effects.

The remaining variables in the productivity equations are fairly standard and not very affected by the choice of innovation variables. Capital intensity has a somewhat low coefficient, albeit reasonable in light of the included industry dummies, which will tend to depress it. Productivity falls with size and age, and in the case of size it reaches a minimum at around 120–160 employees, suggesting that the larger medium-sized firms in Italy are less productive than the smallest or largest.

Our conclusion is that there is a substantial return to both R&D and ICT investments in Italian firms, as they both help to predict innovation and have a large impact on productivity. The median R&D-doing firm in our sample has an R&D-to-sales ratio of 1%. An output elasticity of 0.1, therefore, implies a return of approximately 10 to every euro spent on R&D. For ICT, the number is even higher: the median ICT-investing firm has an ICT-to-sales ratio of 0.2%, which corresponds to a return of 45 for every euro invested in ICT. Given these numbers, it is hard to escape the conclusion that Italian firms may be underinvesting in these activities.

5.4. Testing for complementarity of innovation strategies

Due to the high levels of correlation between the predicted probabilities of process, product, and organizational innovations, it was not possible to include them in the productivity equation to get sensible results. Nevertheless, correlations as high as those reported in Table A5 in the appendix may suggest some degree of complementarity between the different kinds of innovation, which is worth further exploration. To do this, we run some tests of supermodularity on the production function (see Milgrom and Roberts 1990 for a definition of supermodularity). An important result we use for our empirical analysis is that whenever the dimension of the set containing all the combinations of the variables of interest is higher than 2, it is sufficient to check for pairwise complementarity (Topkis 1978, 1998). Recall that in our data we have four variables for innovation outcomes (process innovation, product innovation, process-related organizational innovation, and product-related organizational innovation), all measured with a 0/1 dummy variable: therefore, each combination of innovation outcome can be expressed with a four-element vector like (0,0,0,0), (1,0,0,0), …, (1,1,1,1) for a total of $2^4 = 16$ possibilities. Since we check pairwise supermodularity,

Table 6. Results of complementarity tests using four equation innovation model (process, product, organizational process, and organizational product).

Complementarity test	Test value	F-test	t-Test	p-Value of one-tail t-test	s.e.
Using quadrivariate model of innovation					
Org proc and org prod/without proc and prod	1.323	0.13	0.361	0.359	3.668
Org proc and org prod/without proc, with prod	−2.959	0.42	0.648	0.258	4.566
Org proc and org prod/without prod, with proc	−0.098	0.00	0.032	0.487	3.104
Org proc and org prod/with proc and prod	−0.495	0.18	0.424	0.336	1.166
Prod and org prod/without proc and org proc	−3.262*	2.27	1.507	0.066	2.165
Prod and org prod/without proc, with org proc	−4.398	1.14	1.068	0.143	4.119
Prod and org prod/without org proc, with proc	−4.683	0.61	0.781	0.217	5.996
Prod and org prod/with proc and org proc	−1.934	1.18	1.086	0.139	1.780
Prod and org proc/without proc and org prod	4.281	1.05	1.025	0.153	4.178
Prod and org proc/without proc, with org prod	−0.255	0.07	0.265	0.396	0.964
Prod and org proc/without org prod, with proc	2.860	0.35	0.592	0.277	4.835
Prod and org proc/with proc and org prod	2.209	0.24	0.490	0.312	4.509
Proc and org prod/without prod and org proc	3.505	0.54	0.735	0.231	4.769
Proc and org prod/without prod, with org proc	2.369	1.30	1.140	0.127	2.077
Proc and org prod/without org proc, with prod	−0.777	0.04	0.200	0.421	3.884
Proc and org prod/with prod and org proc	1.972	0.19	0.436	0.331	4.524
Proc and org proc/without prod and org prod	−0.925	0.45	0.671	0.251	1.379
Proc and org proc/without prod, with org prod	−5.461*	1.97	1.404	0.080	3.891
Proc and org proc/without org prod, with prod	−5.207	0.63	0.794	0.214	6.560
Proc and org proc/with prod and org prod	−5.858**	2.89	1.700	0.045	3.446
Proc and prod/without org proc and org prod	0.707	0.90	0.949	0.171	0.745
Proc and prod/without org proc, with org prod	−3.830	0.83	0.911	0.181	4.204
Proc and prod/without org prod. with org proc	−0.429	0.01	0.100	0.460	4.293
Proc and prod/with org proc and org prod	−1.081	0.05	0.224	0.412	4.833

*Significant at 10%.
**Significant at 5%.

we must test 24 inequality constraints.[12] Results, reported in Table 6, indicate that there is no overall complementarity between the four kinds of innovation. If anything, some of the innovation strategies appear to be substitutes, although we are reluctant to draw strong conclusions given the high level of correlation among the predicted innovation dummies, and the fact that with 24 such tests, one would expect that one or two might be significant at the 5% level.

6. ICT and R&D: complements or substitutes?

Despite the difficulties in measuring innovative activity, what emerges from the estimation of the modified CDM model is that both R&D (actual or predicted) and ICT investment make a significant, positive contribution to the firms' ability to innovate and to their productivity. Of course, the channels through which two kinds of investment exert their effects are not the same. As a consequence, the question whether R&D and ICT are complements or substitutes is a legitimate one, especially for a country such as Italy where the presence of small firms is massive and innovation is often embedded in machinery and in technology adoption. In this specific case, we would like to know whether marginal returns to R&D increase as ICT investment increases and vice versa.

As we did in Section 5.4, we perform a supermodularity test to check whether there is complementarity between R&D and ICT with regards to firms' ability to innovate and their productivity. We do this test in two ways: first, as in Section 5.4, we use dummy variables for the presence of R&D and ICT investments. Second, we use predicted or actual log levels of R&D and ICT investment per employee. In the first case, if the returns to ICT and R&D together are higher than the returns to the R&D and ICT alone, we can conclude that they are complementary. In the second case, we merely check the sign and significance of an interaction term between R&D and ICT intensity: if it is positive, the two types of investment are complements in generating innovation or productivity, at least in our data (we cannot check that this result holds everywhere, as would be required for supermodularity).

We first run a bivariate probit where the dependent variables are the presence/absence of R&D and ICT, with a few firm-level control variables (Table A6, columns 1 and 2), to recover the predicted probabilities of doing R&D, ICT, and both, to be used later in the complementarity tests. In the middle two columns of Table A6, the impact of the presence of R&D and ICT investment (actual and predicted) on labor productivity is estimated: the null of no complementarity cannot be rejected.

The same exercise for innovation is reported in Table A7. Again, using both actual and predictions, R&D and ICT turn out to be neither complements nor substitutes, since the value of the test is never significantly different from zero. Essentially, what the table says is that the impact on innovation of adding ICT investment to a firm is not affected whether it does R&D or not. Our interpretation is that while these two kinds of investment are very different from each other – R&D is risky and leads to intangible assets, ICT reflects more an investment and it is basically embodied technological change – they both contribute to the development of innovations and to productivity, but through different channels.

In the final three columns of Table A6, we report the results of the labor productivity regression that includes both R&D and ICT investment, and their interaction. When we use the actual levels of investment or our preferred model with predicted R&D and actual ICT investment, the interaction term is clearly zero, implying no complementarity or substitution. When we include the predicted values of both variables, their coefficients are large and of opposite sign and the interaction term becomes slightly negative. We interpret this result as another manifestation of the limitations of instrumenting two somewhat similar variables using the same set of predictors (as we saw in the case of the innovation variables), and conclude that R&D and ICT are indeed unrelated in their impact on productivity.

7. Conclusions

In this article, we examine the firm-level relationships between product, process, and organizational innovations, productivity, and two of their major determinants, namely R&D and ICT, using data on firms from a single European country, Italy. The element of novelty of our approach is that we treat ICT in parallel with R&D as an input to innovation rather than simply as an input of the production function. By doing this, we acknowledge the existence of possible complementarities among different types of innovation inputs. Our empirical evidence is based on a large unbalanced panel data sample of Italian manufacturing firms in the 1995–2006 period, constructed from the four consecutive waves of the 'Survey on Manufacturing Firms' conducted by Unicredit. We extend the CDM model to include an equation for ICT as an enabler of innovation and organizational innovation as an indicator of innovation output. We find that R&D and ICT both contribute to innovation, even if to a different extent. R&D seems to be the most relevant input for innovation, but if we keep in mind that 34% of the firms in our sample invest in R&D while 68% have investment in ICT, the role of technological change embodied in ICT should not be underestimated. Importantly, ICT and R&D contribute to productivity both directly and indirectly through the innovation equation, but they are neither complements nor substitutes. However, individually they each appear to have large impacts on productivity, suggesting some underinvestment in these activities by Italian firms.

Although we looked briefly at the role of skills in innovation, finding that a simple measure of the white-collar worker share had substantial predictive power and was complementary with R&D, we have been unable to study the role of skills in detail due to data constraints. There is some consensus in the literature about the enabling role of skills with respect to organizational innovation and, in turn, to the effectiveness of ICT investment (Greenan, Topiol-Bensaid, and Mairesse 2001; Bugamelli and Pagano 2004), but we found this difficult to identify using the limited information on organizational innovation available to us.

A relevant, more general result worth to be further explored in the future is related to the way innovation is measured. Although definitions of product, process, and organizational innovations are standardized, being binary variable (yes/no), on one side they fail to measure the height of the innovation step, on the other they do not capture the complexity of the innovation processes within the firm.

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Notes

1. The figure shows ICT investment as a share in gross fixed capital formation from the OECD website for 13 EU countries and the USA. No data are available for Luxembourg and Greece, the remaining members of the EU15.
2. To correct for the use of sequential estimation, we estimate panel bootstrap standard errors for some of our models, and find relatively small increases in the standard errors on the coefficients of the instrumented (predicted) variables.
3. We chose not to treat ICT investment in parallel to R&D because the problem of unobserved ICT investment is not likely to be of the same order of magnitude as that for R&D. Roughly 30% of firms report that they did not invest in ICT during the past three years, and we included a dummy for these firms in the regressions where ICT is included on the right-hand side. Note also that we dropped the few cases where total investment (ICT and non-ICT) was zero.
4. For example, a firm present in all the four waves will have a '1111' code, '1000' if present in the first only, '1100' if in the first and in the second only, and so forth. These codes are transformed into a set of 14 dummies ($2^4 = 16$ minus the 0000 case and the exclusion restriction).
5. We present the general form of the model here, with the four distinct types of innovation. In practice, we found it very difficult to identify their effects separately and later on we explore various reductions of the model to two or three innovation variables only.
6. Since in the empirical specification we take the log of the ICT investment variable (and as a consequence firms with zero ICT investment would turn into missing observation), we add a dummy variable for non-zero ICT investment.

7. In addition to requiring nonmissing data for every variable except R&D and ICT investment, we require that sales per employee be between 5000 and 10 million euros, capital per employee between 200 and 10 million euros, growth rates of employment and sales between −150% and 150%, and investment, R&D, and ICT investment per employee less than 2 million euros. In addition, we restrict the sample by excluding the very few observations where the age of the firm or total investment (ICT and non-ICT) is missing. For further details, see Hall, Lotti, and Mairesse (2008).
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 a semi-parametric extension for non-normal distributions.
9. In the case of a single positive regressor and positive correlation between the disturbances, one can show that the effect of estimating without controlling for selection will indeed be downward bias to the coefficient.
10. In fact, we tested for selection in the ICT and non-ICT investment intensity equations, and found that there was a weak selection effect for the ICT equation and none for the non-ICT equation.
11. The panel bootstrap is implemented by drawing repeated samples of the same size as our panel from our data, using the firm (rather than the observation) as the unit drawn, estimating the entire model recursively on each draw from the data, and averaging the resulting estimates. The number of replications used for this procedure is shown in the tables.
12. For example, to check whether process and product innovations are complementary we must look at four inequalities with all the possible combinations of presence/absence of process- and product-related organizational innovations. For process and product innovations with process- and product-related organizational innovations, the condition to be satisfied is: $QP(1,1,1,1)-QP(1,0,1,1)-QP(0,1,1,1)+QP(0,0,1,1)\geq 0$, where QP(.) is the coefficient corresponding to the predicted probability from the quadrivariate probit used as a dependent variable in the productivity equation. The remaining inequalities are analogous.

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Appendix. Variable definitions

R&D engagement: Dummy variable that takes value 1 if the firm has positive R&D expenditures over the three year of each wave of the survey.
R&D intensity: R&D expenditures per employee (1000 euros), 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 three years of the survey.
Product innovation: Dummy variable that takes value 1 if the firm declares to have introduced a product innovation during the three years of the survey.
Process-related organizational innovation: Dummy variable that takes value 1 if the firm declares to have introduced a process-related organizational innovation during the three years of the survey.
Product-related organizational innovation: Dummy variable that takes value 1 if the firm declares to have introduced a product-related organizational innovation during the three years of the survey.
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 (1000 euros), in logs.

Investment intensity: Investment in machinery per employee (1000 euros), in logs (ICT excluded).
ICT investment intensity: Investment in ICT per employee (1000 euros), in logs (three year average).
Public support: Dummy variable that takes value 1 if the firm has received a subsidy during the three 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.
Share executive and white collar: Number of executive and white-collar employees, divided by the number of employees.
Age: Firm's age (in 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.
Region dummies: A set of indicators for the region where the firm is located (20 variables).
Wave dummies: A set of indicators for firm's presence or absence in the three waves of the survey.

Table A1. Industrial distribution of the sample.

Sector	Firms	Observations	Share non-zero R&D	Share non-zero ICT	Median R&D per employee[a]	Median ICT per employee[a]
Food and beverage	984	1397	27.8%	64.0%	1291.1	342.5
Textiles and apparel	829	1215	33.0%	68.0%	1842.6	322.4
Leather and other	297	427	29.7%	69.6%	1125.9	326.0
Footwear	390	560	31.3%	63.6%	1294.1	196.5
Wood products	275	416	24.3%	65.6%	717.3	271.9
Paper products	295	430	18.1%	65.8%	1067.6	313.0
Publishing and printing	314	429	17.5%	71.1%	1291.1	598.6
Oil refining	43	59	32.2%	66.1%	1700.7	636.0
Chemicals	494	699	46.5%	65.4%	2646.8	438.4
Rubber and plastics	559	818	33.1%	66.6%	1597.4	329.8
Stone, clay, and glass	644	927	27.3%	61.6%	1273.5	230.1
Primary metals	396	610	23.4%	66.2%	1320.1	302.3
Fabricated metals	1217	1756	26.5%	68.8%	1702.4	309.4
Machinery	1423	2142	47.4%	73.1%	1912.8	390.5
Electrical mach and com	419	576	47.7%	74.8%	2086.4	432.8
Electronics	205	293	53.6%	73.7%	2709.8	410.1
Scientific instrument	193	299	56.5%	72.2%	2885.2	499.9
Motor vehicles	204	275	41.5%	74.5%	1275.8	320.9
Rail and trams	94	131	41.2%	70.2%	1812.9	266.8
Misc manufacturing	575	835	34.6%	70.1%	1327.8	299.1
Total	9850	14,294	34.2%	68.3%	1662.7	337.0

Distribution by year

Year	Firms starting in year	Observations	Share non-zero R&D	Share non-zero ICT	Median R&D per employee[a]	Median ICT per employee[a]
1997	4006	4006	29.8%	69.0%	1335.7	344.8
2000	2887	4065	35.6%	80.8%	1519.0	322.8
2003	1460	3451	41.2%	68.5%	1443.9	298.6
2006	1497	2772	30.0%	48.9%	3296.1	446.9
Total	9850	14,294	34.2%	68.3%	1662.7	337.0

[a]In euros, for firms with non-zero values.

Table A2. Sample distribution by region and year.

								Shares			
Area	Code	Region	1998	2001	2004	2007	Total	R&D doer	ICT	Innovator	Org. innov
1	1	Piemonte	407	386	324	294	1411	39.1%	70.0%	64.4%	31.5%
1	2	Valle d'Aosta	4	4	5	2	15	60.0%	73.3%	60.0%	46.7%
1	3	Liguria	45	41	39	28	153	37.9%	73.9%	64.1%	25.5%
1	4	Lombardia	1179	1100	919	848	4046	35.4%	69.4%	64.4%	30.2%
2	5	Trentino Alto Adige	40	49	55	32	176	39.8%	71.6%	69.9%	35.8%
2	6	Veneto	579	492	465	347	1883	34.3%	73.2%	65.5%	29.1%
2	7	Friuli Venezia	136	118	116	92	462	37.7%	70.1%	63.0%	32.9%
2	8	Emilia Romagna	429	486	464	340	1719	38.2%	66.6%	61.7%	27.9%
3	9	Marche	158	192	145	122	617	31.6%	69.5%	61.9%	25.4%
3	10	Toscana	408	481	327	224	1440	32.6%	64.0%	59.0%	26.3%
3	11	Umbria	34	59	51	52	196	40.3%	66.8%	65.8%	30.1%
3	12	Lazio	79	97	86	70	332	33.4%	66.6%	63.0%	34.9%
4	13	Campania	121	173	124	87	505	27.1%	68.9%	60.2%	23.6%
4	14	Abruzzo	85	93	109	60	347	28.2%	63.7%	60.2%	23.9%
4	15	Molise	15	10	11	7	43	30.2%	53.5%	55.8%	27.9%
4	16	Puglia	110	136	84	71	401	22.2%	60.3%	58.9%	23.9%
4	17	Basilicata	16	9	10	8	43	20.9%	62.8%	51.2%	30.2%
4	18	Calabria	9	17	14	12	52	19.2%	69.2%	57.7%	21.2%
4	19	Sicilia	105	84	69	39	297	18.5%	62.6%	56.9%	21.5%
4	20	Sardegna	47	38	34	37	156	19.9%	57.1%	62.2%	32.1%
		Total	4006	4065	3451	2772	14,294	34.3%	68.3%	62.9%	28.8%
Sample distribution by broad area and year											
1		Northwest	1635	1531	1287	1172	5625	36.5%	69.7%	64.4%	30.4%
2		Northeast	1184	1145	1100	811	4240	36.5%	70.1%	63.8%	29.3%
3		Central	679	829	609	468	2585	33.1%	65.9%	60.7%	27.5%
4		South	508	560	455	321	1844	24.0%	63.6%	59.2%	24.3%
		Total	4006	4065	3451	2772	14,294	34.3%	68.3%	62.9%	28.8%

Table A3. R&D equation with selection.

Dependent variable	(1) Probit prob R&D non-zero	(2) OLS log R&D per employee	(3) Sample selection model prob R&D non-zero	(4) Log R&D per employee
Log employment	0.232***	−0.326***	0.233***	−0.242***
	(0.016)	(0.026)	(0.016)	(0.028)
Log employment squared	−0.037***	0.075***	−0.036***	0.060***
	(0.007)	(0.011)	(0.007)	(0.011)
Log age	0.021	−0.056*	0.020	−0.050*
	(0.018)	(0.029)	(0.018)	(0.028)
Log age squared	−0.003	0.012	−0.005	0.011
	(0.018)	(0.029)	(0.018)	(0.028)
D (large firm competitors)	0.057**	0.024	0.058**	0.044
	(0.025)	(0.038)	(0.025)	(0.038)
D (regional competitors)	0.031	−0.123	0.032	−0.108
	(0.047)	(0.080)	(0.048)	(0.082)
D (national competitors)	0.126***	−0.135*	0.125***	−0.083
	(0.041)	(0.070)	(0.042)	(0.071)
D (European competitors)	0.388***	0.079	0.387***	0.224***
	(0.046)	(0.075)	(0.047)	(0.079)
D (international competitors)	0.444***	0.172**	0.447***	0.330***
	(0.048)	(0.079)	(0.049)	(0.081)
D (received subsidies)	0.307***	0.293***	0.309***	0.400***
	(0.026)	(0.041)	(0.026)	(0.041)
D (member of a group)	0.079**	0.218***	0.081***	0.243***
	(0.030)	(0.045)	(0.030)	(0.045)
Chi-squared (5) for selection		34.1***		
		(0.000)		
Standard error		1.212	1.279***	
			(0.021)	
Correlation coefficient	0.0		0.416***	
			(0.042)	
Number of observations (non-zero)	14,294		14,294	
	(4896)		(4896)	
Loglikelihood	−8218.99	−7853.68	−16,067.6	

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern. Estimates obtained using TSP 5.1. The first, third, and fourth columns show chi-squared tests, and the second shows *F*-tests.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table A4. Probability of innovating.

Dependent variable	Quadrivariate probit			
	Innovation		Organizational innovation	
	Process	Product	Process	Product
Predicted R&D intensity (in logs)	0.426***	0.568***	0.505***	0.492***
	(0.043)	(0.043)	(0.045)	(0.049)
ICT investment per employee (in logs)	0.000	0.030***	0.012	0.061***
	(0.011)	(0.011)	(0.012)	(0.013)
D (no ICT investment)	−0.286***	−0.291**	−0.372***	−0.383***
	(0.028)	(0.028)	(0.031)	(0.034)
Investment per employee (in logs)	0.122***	0.035***	0.059***	0.023**
	(0.010)	(0.010)	(0.011)	(0.012)
D (no investment)	−0.132***	−0.080***	−0.116***	−0.090***
	(0.037)	(0.038)	(0.043)	(0.047)
Log employment	0.236***	0.280***	0.255***	0.255***
	(0.016)	(0.016)	(0.017)	(0.019)
Log employment squared	−0.035***	−0.053***	−0.055***	−0.053***
	(0.007)	(0.007)	(0.008)	(0.008)
Log age	0.008	0.065***	0.029	0.038*
	(0.018)	(0.019)	(0.019)	(0.022)
Log age squared	0.004	−0.011	−0.029	−0.031
	(0.017)	(0.018)	(0.019)	(0.020)
Employees at max (s.e.)	1246	660	477	521
Number of observations	14,294			
Log likelihood	−27,388.3			

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table A5. Correlation of innovation variables.

	Process innovation	Product innovation	Process-related organizational change	Product-related organizational change
Actual				
Process innovation	1.000			
Product innovation	0.292	1.000		
Process-related organizational change	0.346	0.128	1.000	
Product-related organizational change	0.163	0.412	0.433	1.000
Predicted latent variables[a]				
Process innovation	1.000			
Product innovation	0.400	1.000		
Process-related organizational change	0.587	0.462	1.000	
Product-related organizational change	0.466	0.893	0.719	1.000
Predicted probabilities[a]				
Process innovation	1.000			
Product innovation	0.396	1.000		
Process-related organizational change	0.674	0.285	1.000	
Product-related organizational change	0.446	0.859	0.544	1.000
Estimated correlation of the disturbances[a]				
Process innovation	1.000			
Product innovation	0.449	1.000		
Process-related organizational change	0.551	0.184	1.000	
Product-related organizational change	0.295	0.624	0.640	1.000

[a]These are computed from the estimates of the quadrivariate probit model for innovation shown in Table 4.

Table A6. Performing formal R&D and ICT investment: complementarity tests for productivity.

Dependent variable	Bivariate probit		Labor productivity R&D and ICT dummies		Labor productivity R&D and ICT continuous		
	R&D	ICT	Actual	Predicted	Actual	Predicted	R&D pred, ICT act
R&D investment			0.090***	2.305***	0.055***	−0.341***	0.104***
			(0.023)	(0.400)	(0.011)	(0.057)	(0.023)
ICT investment			0.005	−1.554***	0.066***	1.015***	0.096***
			(0.014)	(0.195)	(0.008)	(0.008)	(0.006)
R&D*ICT			0.072***	−0.557***	0.009	−0.069**	0.009
			(0.016)	(0.119)	(0.007)	(0.035)	(0.009)
Test for complementarity			−0.023	−1.308***			
			(0.026)	(0.358)			
Log capital per employee			0.157***	0.158***	0.140***	0.154***	0.139***
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log employment	0.232***	0.198***	−0.094***	−0.076***	−0.080***	−0.067***	−0.065***
	(0.016)	(0.016)	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)
Log employment squared	−0.037***	−0.058***	0.040***	0.015***	0.036***	0.011***	0.030***
	(0.007)	(0.007)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Log age	0.020	0.040**	−0.028***	−0.011	−0.028***	−0.067***	−0.023**
	(0.018)	(0.019)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Log age squared	−0.003	0.012	−0.005	0.003	−0.006	−0.012	−0.007
	(0.018)	(0.018)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
D (large firm competitors)	0.057**	0.051**					
	(0.025)	(0.025)					
D (regional competitors)	0.030	0.124***					
	(0.048)	(0.044)					
D (national competitors)	0.123***	0.178***					
	(0.042)	(0.039)					
D (European competitors)	0.385***	0.310***					
	(0.047)	(0.046)					
D (international competitors)	0.440***	0.332***					
	(0.049)	(0.049)					
D (received subsidies)	0.309***	0.227***					
	(0.026)	(0.027)					

(*continued*)

Table A6. Continued.

Dependent variable	Bivariate probit		Labor productivity R&D and ICT dummies		Labor productivity R&D and ICT continuous		
	R&D	ICT	Actual	Predicted	Actual	Predicted	R&D pred, ICT act
D (member of a group)	0.079***	−0.014					
	(0.030)	(0.031)					
Rho	0.243***						
	(0.015)						
Log likelihood	−16,239.9						
Standard error (R-squared)			0.606	0.605	0.597	0.602	0.598
			(0.239)	(0.241)	(0.261)	(0.248)	(0.258)
Number of obs non-zero	4896	9678	14,294	14,294	14,294	14,294	14,294

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. The first two columns show the results of a bivariate probit for doing R&D and having ICT investment. The next two columns are complementarity tests using the predicted and actual dummies for having R&D and ICT. The last two columns perform the test using the levels of R&D and ICT together with dummies for their absence. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

Table A7. Innovation as a function of performing formal R&D and ICT investment: complementarity tests.

	Probit for innovation									
Dependent variable	Process		Product		Orgaizational process		Organizational product		Any innovation	
R&D and ICT dummies	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
R&D investment non-zero	0.469***	0.377	0.737***	1.229	0.350***	2.660***	0.466***	1.065	0.825***	1.952**
	(0.048)	(0.802)	(0.048)	(0.827)	(0.054)	(0.902)	(0.058)	(0.962)	(0.053)	(0.873)
ICT investment non-zero	0.243***	1.215***	0.191***	0.051	0.337***	1.034**	0.259***	0.394	0.282***	0.803*
	(0.029)	(0.402)	(0.031)	(0.414)	(0.035)	(0.452)	(0.041)	(0.508)	(0.029)	(0.415)
Both R&D and ICT non-zero	0.716***	2.160***	0.929***	2.304***	0.692***	2.314***	0.781***	2.216***	1.117***	2.699***
	(0.034)	(0.250)	(0.034)	(0.255)	(0.037)	(0.278)	(0.041)	(0.309)	(0.037)	(0.260)
ICT inv. per employee (in logs)	0.128***	0.119***	0.045***	0.040***	0.068***	0.059***	0.040***	0.035***	0.119***	0.106***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.009)
D (no ICT investment)	−0.113***	−0.210***	−0.027	−0.124***	−0.076*	−0.180***	−0.030	−0.137***	−0.146***	−0.257***
	(0.037)	(0.034)	(0.038)	(0.037)	(0.043)	(0.043)	(0.049)	(0.047)	(0.038)	(0.034)
Log employment	0.136***	0.009	0.139***	−0.009	0.154***	−0.007	0.139***	−0.011	0.149***	−0.021
	(0.015)	(0.022)	(0.015)	(0.023)	(0.016)	(0.024)	(0.018)	(0.027)	(0.015)	(0.023)
Log employment squared	−0.007	0.020**	−0.013*	0.005	−0.022***	0.001	−0.011	0.01	−0.023***	0.002
	(0.006)	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.011)	(0.007)	(0.010)
Log age	−0.019	−0.040**	0.032*	0.018	−0.003	−0.017	0.019	0.002	−0.007	−0.024
	(0.018)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)	(0.023)	(0.019)	(0.019)
Log age squared	0.010	0.005	−0.007	−0.008	−0.026	−0.026	−0.034	−0.037*	−0.002	−0.005
	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)	(0.019)	(0.021)	(0.021)	(0.018)	(0.018)
Test for complementarity (standard error)	0.004	0.578	0.001	1.024	0.005	−1.380	0.056	0.757	0.010	−0.056
	(0.066)	(0.931)	(0.066)	(0.955)	(0.074)	(1.047)	(0.082)	(1.131)	(0.071)	(1.001)
Log likelihood	−8851.9	−9045.0	−8283.8	−8677.0	−7302.2	−7407.3	−5469.3	5617.4	−7753.6	−8209.3
Pseudo *R*-squared	0.106	0.087	0.133	0.091	0.073	0.059	0.094	0.069	0.142	0.092
Number of observations	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294

Notes: Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level. Industry, wave, regional, and time dummies are included in all equations. Reference groups: *D* (provincial competitors), Lombardia, year 1997, first wave pattern.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.