Evidence on the Impact of R&D and ICT Investment on Innovation and Productivity in Italian Firms

Bronwyn H. Hall,[#] Francesca Lotti,[§] and Jacques Mairesse[♦]

March 31st, 2011

Abstract

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 United States. In this paper we investigate 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, together with a version of the CDM model (Crepon *et al.*, 1998) 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 both contribute to innovation, even if to a different extent: R&D seems to be the most relevant input for any kind of innovation; productivity is affected by both inputs. Moreover, there is no complementarity between R&D and ICT, neither for innovation, nor for productivity.

Keywords: R&D, ICT, Innovation, Productivity, Complementarity, Italy.

JEL classification: L60, O31, O33.

[#] University of California at Berkeley, Maastricht University, NBER, and IFS. Deparment of Economics, 549 Evans Hall, Berkeley, CA 94720-3880.

[§] Economic Research Department, Bank of Italy. Via Nazionale 91 – 00184 Rome, Italy. Email: francesca.lotti@bancaditalia.it

[♦] CREST (ENSAE, Paris), UNU-MERIT (Maastricht University), and NBER. 15, Boulevard Gerbiel Peri, 92245 Malakoff Cedex, France.

1. *Introduction**

Both Research and Development (R&D) and Information and Communication Technology (ICT) investment have been identified as areas of relative underperformance in Europe vis-à-vis the United States. For example, Van Ark *et al.* (2003) concluded the following in their study of the reasons for lower productivity growth in Europe: "The results 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." 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 United States. Figure 1 shows the R&D investment-GDP and ICT investment-GDP shares for the EU15 and the United States 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 their productivity is low, or are there other causes for this low investment?

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

* We would like to thank the Unicredit research department for having kindly supplied firm level data for this project, in particular E. D'Alfonso, A. Pasetto, and T. Riti. We also thank Rachel Griffith, Steve Bond, and Marco Vivarelli for useful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the Bank of Italy.

in processing and the organization of work within the firm (e.g., Greenan *et al.*, 1996). To our knowledge, very few papers have investigated R&D and ICT investment jointly and tried to assess their relative importance and to what extent they are complements or substitutes. The few papers 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 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 paper we use a version of the well-known model of R&D, innovation, and productivity that is due to Crepon, Duguet, and Mairesse (1998) 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.

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 the current paper directs its attention to data on Italian firms.

Taking advantage of our previous work (Hall, Lotti and Mairesse 2008 and 2009), and in the spirit of Polder *et al.* (2009), we rely on an extension of a modified version of the

---

[1] The figure shows ICT investment as a share in gross fixed capital formation from the OECD website for 13 EU countries and the United States. No data is available for Luxembourg and Greece, the remaining members of the EU15.

CDM model (Griffith *et al.*, 2006) 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. 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 paper reviews the micro-econometric evidence on the use of information and communication technology 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, i.e. the fact that "computers were visible everywhere except in the productivity statistics" (Solow, 1985).

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 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, Brynjolfsson and Yang 1998, Brynjolfsson *et al.* 2002), ICT use at the firm level (number of PCs, the use of network, number of employees using ICT; Greenan and Mairesse, 1996) 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 *et al.* (2002) for the US, Greenan *et al.* (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 (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, like retraining of workers, consultants, management time. See also Brynjolfsson *et al.* (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 turns, 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 (like 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 a structural model based on the “CDM” framework (Crépon-Duguet-Mairesse, 1998). Crépon, Duguet and Mairesse (1998) propose a model of the relationship among innovation input, innovation output and productivity. The 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 three-step model following the logic of firms’ decisions and outcomes in terms of innovation. In the first step, firms decide whether to engage in R&D or not and the amount of resources to invest. Given the firm’s decision to invest in innovation, the second step is characterized by a knowledge production function (as in Pakes and Griliches, 1984) in which innovation output stems from innovation input and other input factors. In the third step, an innovation augmented Cobb-Douglas production function describes the effect of innovative output on the firm’s labor 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 find positive effects of product and process innovation when combined with organizational innovation in both sectors.

3. The extended CDM model

The model we use has three blocks. The first consists of the decision whether to invest in R&D, and how much to spend on the investment.[2] The second consists of a set of

[2] 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 per cent of firms report that they did not invest in ICT during the past three years, and we included a dummy for

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, ICT, and physical capital. 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.[3] 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 cases with more than one year per firm (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 inconsequential. The following subsections discuss the models estimated in more detail.

---

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.

[3] 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 fourteen dummies ($2^4 = 16$ minus the 0000 case and the exclusion restriction).

3.1. The R&D decision

In this first stage, 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 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:

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

DX_i is an (observable) indicator function that takes 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 ε_i 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 (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 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 3 in the Appendix. Unlike the case in Hall et al. (2009), which 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, as in the original CDM model, 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 SMEs, which represent nearly 90% of our sample. The outcomes of the knowledge production function are four types of innovation: product, process, and organizational innovation associated with either of these:[4]

$$INNO_i^j = \gamma_j RD_i^* + \gamma_j^{ICT} ICT_i + \gamma_j^I I_i + x_i \delta_j + u_{ji} \qquad j = 1, \ldots, 4, \tag{4}$$

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, and I_i is ordinary investment intensity, x_i is the set of common covariates plus a dummy for zero ICT investment, 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.

Equation (4) is estimated as a quadrivariate probit model using the GHK algorithm (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 various bivariate and trivariate probit versions of the model.

[4] We present the general form of the model here, with the four distinct types of innovation. In practice we found the effects difficult to identify separately and later on we explore various reductions of the model to 2 or 3 innovation variables only.

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:

$$y_i = \pi_1 k_i + INNO_i^* \pi_2 + Z_i \psi + v_i \tag{5}$$

where y is labor productivity (sales per employee, in logs), k is the log of capital per worker, $INNO^*$ is a set of predicted probabilities 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 innovation, 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, 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 firm size. We merged the data from these four surveys, excluding firms with incomplete information or with extreme observations for the variables of interest.[5]

Our final sample is an unbalanced panel of 14,294 observations on 9,850 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 to R&D, less than one thousand euros per employee.

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% to 27%). For 27% of the firms product and process innovations go together, while 24% are process innovators only. 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.

---

[5] In addition to requiring nonmissing data for everything 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 per cent and 150 per cent, 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).

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 (OLS) for R&D intensity, adding to this equation the predicted probabilities from the R&D decision equation, the 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".[6] The probability terms were jointly significant, with a $\chi^2(5) = 33.8$. We therefore concluded that selection bias was present and estimated the full two equation model by maximum likelihood (the final two columns of Table A3). The results confirmed the presence of selection, with a highly

[6] 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.

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 towards zero in general, but did not have much effect on their significance (compare columns 2 and 4 of Table A3). 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 per cent), as do firms that are members of a group or who receive subsidies of some kind. This last result suggests 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 ordinary least squares. 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 important an issue for these kinds of investment, both because they are more easily tracked, and also because they do not exhibit the same kind of threshold effects arising from sunk costs.[7] 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 to 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 per cent and receiving subsidies (which are often investment subsidies) increases non-ICT investment by 40 per cent. Interestingly, there is regional variation in R&D and ICT investment, but not in ordinary investment.

Based on the results of this exploration of selection issues in the reporting of the three types of investment, in the next section of the paper we will use the predicted values of R&D intensity (the expectation of R&D intensity conditional on the other firm

[7] 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.

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 byproduct of other activities and may not be separately tracked.

5.2. The innovation equations

Table 4 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 investment, 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 innovation, but not with process innovation, although not having any ICT investment is strongly negative for process innovation. Older firms are more likely to product-innovate, but the age of the firm is not associated strongly to other types of innovation. Finally, the residual correlation of the innovation variables after controlling for these factors is much higher than the raw correlations, suggesting that the firms have a strong idiosyncratic tendency towards 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, process (product) related innovation is highly correlated with process (product) innovation. 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 4. As one can observe, correlations are nearly doubled with respect to the actual values, ranging from 0.25 to a 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. Moreover, 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 combination in reasonable numbers, 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 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 to 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. To explore this issue, we will perform possible complementarity tests between the different kinds of innovation in the next section.

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 including a measure of ICT investment, and for two alternative indicators of innovation activities: a dummy variable for any kind of innovation and the predicted probability of any innovation as coming from column (5) of Table 4.

Conventional variables (capital, investment, employment and firm's age) are included in each specification. The first column show results for a basic specification without indicators of innovation activity, but with the predicted R&D intensity and the actual ICT intensity as proxies for the innovative effort. They both show a positive effect on productivity, slightly higher for R&D. When ICT investment is included, investment exerts a lower impact on productivity, even if it is barely significant.

The dummy variable for the actual presence of any kind of innovation (column 2) would suggest that innovation has no effect on productivity, while if we proxy innovation with the predicted probability of any innovation we find a positive effect: doing any kind of innovation increases productivity nearly 20 percent (column 3). Using the predicted probability instead of the actual presence/absence of innovation is more appropriate to account for possible endogeneity issues concerning knowledge inputs.

Nevertheless, when we include ICT investment in the productivity equation (column 4), the predicted probability of innovation activity looses its significance; ICT per employee itself is a better predictor of productivity gains than the probability of innovation predicted by ICT and R&D investment. This result is similar to a previously documented result in Mairesse et al (2005), who found that R&D per employee was a better predictor of productivity than the probability of innovation predicted by R&D. Essentially, continuous variables measured in currency units are simply much better at describing individual innovative firm behavior than simple dummy variables, even if those variables have been instrumented.

The remaining variables in the productivity equations are fairly standard and not affected by the choice of innovation variables. Capital intensity has a somewhat low (but reasonable in light of the included industry dummies, which tend to depress it) coefficient. Productivity falls with size and age, and in the case of size it reaches a minimum at around 140 employees, suggesting that the larger medium-sized firms in Italy are less productive than the smallest or largest.

Due to the high levels of correlation between the predicted probabilities of process, product and organizational innovation, it was not possible to include them in the productivity equation to get sensible results. Nevertheless, high correlations as the ones reported on 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 and 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, we must test 24 inequality constraints.[8] Results, reported on Table 6, indicates that there is no overall complementarity between the four kinds of innovation. In fact, the only significant tests are negative, those between process (product) and process (product) related organizational innovation. The negative signs of those coefficients suggest that a combination of process (product) and process (product) related organizational innovation may have a disruptive effect right after their introduction, even if they are likely to lead to productivity gains in the future.

[8] For example to check whether process and product innovation are complementary we must look at 4 inequalities with all the possible combinations of presence/absence of process and product related organizational innovation. For process and product innovation with process and product related organizational innovation the condition to be satisfied is: $QP(1,1,1,1)-QP(1,0,1,1)-QP(0,1,1,1)+QP(0,0,1,1)\leq 0$, 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.

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

Despite the difficulties in measuring correctly innovation 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 like 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 the previous section, 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. Like in the previous section we use dummy variables for the presence of R&D and ICT investment. If the productivity or innovation probability increases from investing in ICT and formal R&D together are higher than they are when only one type of these investments is undertaken, we can conclude that they are complementary. 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 alone, ICT alone, and doing both, to be used later in the complementarity tests. In the last 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 on 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. 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.

7. Conclusions

In this paper we examine the firm level relationships between product, process and organizational innovation, 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 per cent of the firms in our sample invest in R&D while 68 per cent 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.

One aspect that has been left aside from the analysis is the relevance of skills, mostly due to data constraints, though there is consensus in the literature about the enabling role of skills with respect to organizational innovation and, in turns, to the effectiveness of ICT investment (Greenan et al, 2001, Bugamelli and Pagano, 2004).

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 innovation 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.

References

Black, S. E., and L. M. Lynch (2001). "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity," *Review of Economics and Statistics* 83(3), 434–45.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002). "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics* 117(1), 339–76.

Brynjolfsson, E., and L. M. Hitt (1995). "Information Technology as a Factor of Production: The Role of Differences Among Firms," *Economics of Innovation and New Technology* 3 (January).

Brynjolfsson, E., and L. M. Hitt (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives* 14 (4), 23-48.

Brynjolfsson, E., L. M. Hitt, and S. Yang (2002). Intangible Assets: Computers and Organizational Capital. *Brookings Papers on Economic Activity* 1, 137-199.

Brynjolfsson, E., and S. Yang (1998). The Intangible Benefits and Costs of Computer Investments: Evidence from the Financial Markets. MIT Sloan School and Stanford Graduate School of Business. Manuscript.

Bugamelli, M. and P. Pagano (2004), "Barriers to Investment in ICT", Applied Economics, 36(20), pp. 2275-2286.

Castiglione C. (2009). "ICT Investment and Firm Technical Efficiency", paper presented at EWEPA 2010, Pisa, June.

Cerquera D. and G. J. Klein (2008). "Endogenous Firm Heterogeneity, ICT and R&D Incentives", ZEW Discussion Paper No. 08-126.

Crépon B., E. Duguet and J. Mairesse (1998). Research, Innovation and Productivity: An Econometric Analysis at the Firm Level, *Economics of Innovation and New Technology*, 7(2), 115-158.

Draca M., R. Sadun and J. Van Reenen (2007). Productivity and ICT: A Review of the Evidence, in Mansell, R., C. Avgerou, D. Quah and R. Silverstone (Eds.), *The Oxford Handbook of Information and Communication Technologies*, Oxford University Press.

Greenan, N., and J. Mairesse (2000). Computers and productivity in France: Some evidence. *Economics of Innovation and New Technology*, 9(3), 275-315.

Greenan N., A. Topiol-Bensaid and J. Mairesse (2001). "Information Technology and Research and Development Impacts on Productivity and Skills: Looking for Correlations on French Firm Level Data", in *Information Technology, Productivity and Economic Growth*, M. Pohjola ed., Oxford University Press, 119-148.

Greene, W.H. (2003). *Econometric Analysis*, 5th ed. Upper Saddle River, NJ: Prentice-Hall, pp. 931-933.

Griffith R., E. Huergo, B. Peters and J. Mairesse (2006). "Innovation and Productivity across Four European Countries", *Oxford Review of Economic Policy*, 22(4), 483-498.

Hall, B. H. and J. Lerner (2010). "The Financing of R&D and Innovation." In Hall, B. H. and N. Rosenberg, *Handbook of the Economics of Innovation*, Elsevier, forthcoming April.

Hall B. H., F. Lotti and J. Mairesse (2008). "Employment, Innovation and Productivity: Evidence from Italian MicroData", *Industrial and Corporate Change*, 17 (4), 813-839.

Hall B. H., F. Lotti and J. Mairesse (2009). "Innovation and Productivity in SMEs: Empirical Evidence for Italy", *Small Business Economics*, 33, 13-33.

Hall B. H. and J. Mairesse (2009). “Corporate R&D Returns,” Knowledge Economists’ Policy Brief N° 6, DG Research, European Commission.

Mairesse, J. and Y. Kocoglu (2005), “Issues in Measuring Knowledge: The Contribution of R&D and ICT to Growth,” Paper presented at the Advancing Knowledge and the Knowledge Economy conference, National Academies, Washington, DC.

Mairesse, J., P. Mohnen, and E. Kremp (2005), “The Importance of R&D and Innovation for Productivity: A Reexamination in Light of the 2000 French Innovation Survey”, *Annales d'Economie et de Statistique* 79-80: 487-528

Mansfield, E. (1968), *Industrial Research and Technological Innovation: an Econometric Analysis,* W.W. Norton & Co, New York.

Milgrom, P. and J. Roberts (1990), “The Economics of Modern Manufacturing, Technology, Strategy and Organizations”, *American Economic Review*, 80, 511-528.

Moncada-Paternò-Castello, P., C. Ciupagea, K. Smith, A. Tübke and M. Tubbs (2009). “Does Europe perform too little corporate R&D? A comparison of EU and non-EU corporate R&D performance,” Seville, Spain: IPTS Working Paper on Corporate R&D and Innovation No. 11.

O’Sullivan, M. (2006). “The EU’S R&D Deficit and Innovation Policy,” Report of the Expert Group of Knowledge Economists, DG Research, European Commission.

Polder M., G. Van Leeuwen, P. Mohnen and W. Raymond (2009). “Productivity Effects of Innovation Modes”, Statistics Netherlands Discussion Paper n° 09033.

Topkis, D.M. (1978). “Minimizing a Submodular Function on a Lattice”, *Operations Research*, 26, 305–321.

Topkis, D.M. (1998), “Supermodularity and complementarity”, In: Kreps, D.M., Sargent, T.J., Klemperer, P. (Eds.), *Frontiers of Economic Research Series*. Princeton Univ. Press, Princeton.

Van Ark B., R. Inklaar and R. H. McGuckin (2003). “ICT and productivity in Europe and the United States: Where do the differences come from?,” CESifo Economic Studies, Vol. 49 (3), 295-318.

Van Reenen J. and L. Chennells (2002). "The Effects of Technological Change on Skills, Wages and Employment: A Survey of the Micro-econometric Evidence ", in *Productivity, Inequality and the Digital Economy: A Transatlantic Perspective*, N. Greenan, Y. Lhorty and J. Mairesse eds., MIT Press, 175-225.

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 (thousand 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 (thousand Euros), in logs.

Investment intensity: investment in machinery per employee (thousand Euros), in logs (ICT excluded).

ICT investment intensity: investment in ICT per employee (thousand 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.

Age: firm's age (in years).

Industry dummies: a set of indicators for a 2-digits 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

Figure 1

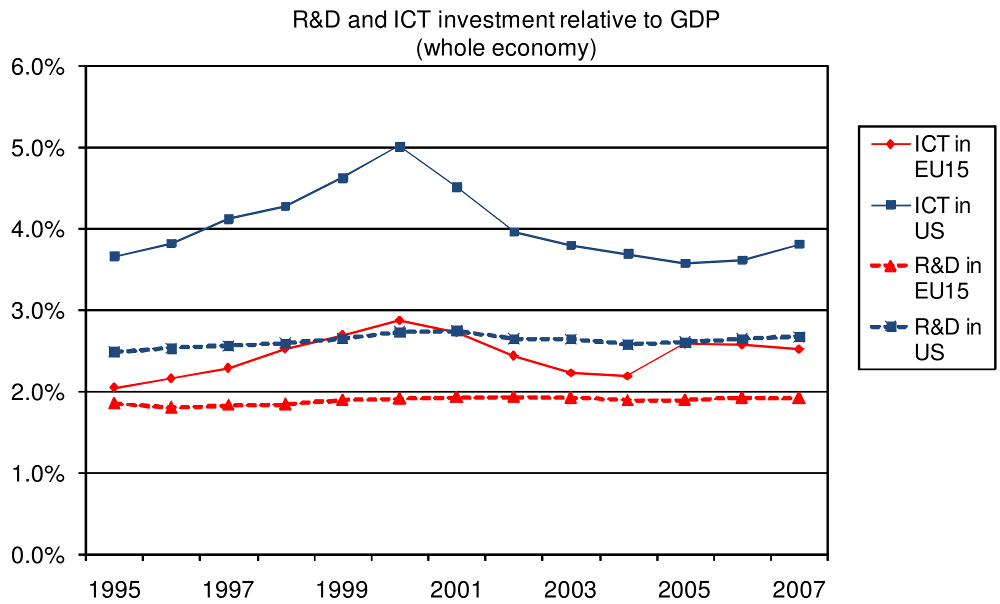

Figure 2

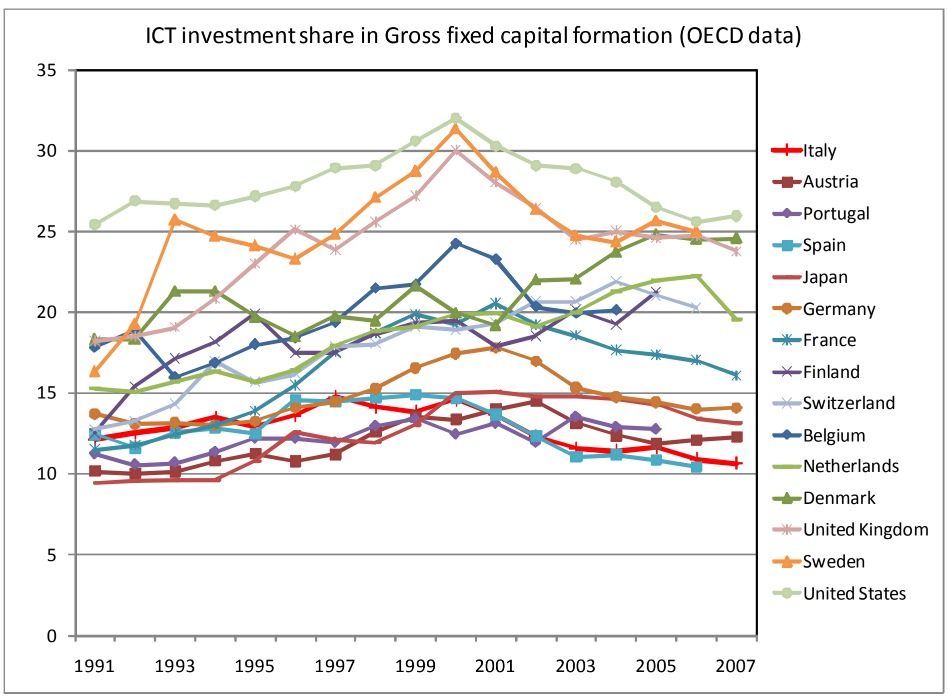

Table 1 - Descriptive statistics, unbalanced sample.

Period: 1995-2006			
Num. of observations (firms)	14,294 (9,850)	Firms with large firms as competitors	39.1%
N. 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 EU competitors	17.4%
Firms with non-ICT investment	84.2%	Firms with international competitors	14.0%
Firms with R&D	34.2%	Firms within a group	24.7%
Firms with ICT	68.3%	Firms subsidies' recipients	37.2%
		Firms with product innovation	38.9%
non-ICT investment intensity for firms that invest* (mean/median)	8.64/ 4.54	Firms with process innovation	50.9%
R&D intensity for R&D-doers* (mean/median)	3.79/ 1.63	Firms with both product and process innovation	26.9%
ICT intensity for ICT investors* (mean/median)	0.79/ 0.34	Firms with organizational innovation for product innovation	15.0%
Average capital intensity* (mean/median)	52.0/ 25.8	Firms with organizational innovation for process innovation	24.0%
Labor productivity* (mean/median)	219.5/ 157.8	Firms with high skill intensity	39.0%

*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			Org 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	4,683	32.8%	32.8%	13.8%	27.7%
Process only	2,199	15.4%	48.1%	12.1%	15.5%
Product and process	2,087	14.6%	62.7%	20.1%	14.6%
All (prod/proc/org)	1,755	12.3%	75.0%	22.1%	15.3%
Process and organizational	1,234	8.6%	83.7%	9.7%	10.3%
Product only	1,212	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	5,554	38.9%		60.0%	41.8%
Any process innovation	7,275	50.9%		64.1%	55.7%
Any organizational change	4,113	28.8%		42.0%	34.4%

Innovation dummy patterns	Obs	Share
None	4683	32.8%
Process only	2,199	15.4%
Process and product only	2,087	14.6%
All four types together	1,278	8.9%
Product only	1,212	8.5%
Process and org process only	1,148	8.0%
Org process only	426	3.0%
Product and org product only	401	2.8%
Process, product, and org process	336	2.4%
Process, product, and org product	141	1.0%
Org process or product only	102	0.7%
Org product only	96	0.7%
Product and org process only	63	0.4%
Process and org product only	47	0.3%
Process and both organizational	39	0.3%
Product and both organizational	36	0.3%

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

	Sample selection	OLS	OLS
Dependent variable	Log R&D	Log ICT	Log investment
	per employee	per employee	per employee
Log employment	-0.241***	-0.126***	-0.072***
	(0.029)	(0.019)	(0.018)
Log employment squared	0.060***	0.045***	0.040***
	(0.012)	(0.009)	(0.007)
Log age	-0.056*	0.031	-0.025
	(0.029)	(0.021)	(0.020)
Log age squared	0.011	0.007	0.003
	(0.029)	(0.020)	(0.020)
D(Large firm competitors)	0.044	0.014	0.028
	(0.039)	(0.027)	(0.026)
D(Regional competitors)	-0.107	-0.080	0.019
	(0.082)	(0.057)	(0.050)
D(National competitors)	-0.080	-0.007	-0.031
	(0.072)	(0.050)	(0.044)
D(European competitors)	0.226***	0.067	0.008
	(0.079)	(0.056)	(0.050)
D(International competitors)	0.330***	0.086	0.010
	(0.082)	(0.058)	(0.052)
D(Received subsidies)	0.398***	0.089***	0.406***
	(0.043)	(0.028)	(0.027)
D(Member of a group)	0.240***	0.239***	0.099***
	(0.047)	(0.035)	(0.033)
Chisq or F-test for competitor vars#	80.3***	3.3***	0.8
Chisq or F-test for industry dummies	277.9***	7.3***	32.2***
Chisq or F-test for regional dummies	68.9***	3.6***	1.3
Chisq or F-test for time dummies	224.6***	15.0***	35.6***
Chisq or F-test for wave dummies	18.3	4.8***	3.3***
Standard error	1.278 (0.022)	1.237	1.283
R-squared	0.175	0.059	0.100
Number of observations	4,896	9,678	12,034

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.
* = significant at 10%, ** = significant at 5%, *** = significant at 1% .
Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.
The first column shows a chi-squared test, and the others show F-tests.

Table 4 - Probability of Innovating

	Quadrivariate probit				Univariate probit
Dependent variable	Innovation		Organizational innovation		Any innovation
	Process	Product	Process	Product	
Predicted R&D intensity	0.434***	0.571***	0.510***	0.496***	0.218***
(in logs)	(0.043)	(0.043)	(0.045)	(0.049)	(0.016)
ICT inv. per employee	0.018	0.039***	0.024**	0.070***	0.016***
(in logs)	(0.011)	(0.011)	(0.012)	(0.013)	(0.004)
D (no ICT investment)	-0.306***	-0.298**	-0.385***	-0.389***	-0.144***
	(0.027)	(0.028)	(0.031)	(0.034)	(0.011)
Investment per employee	0.095***	0.019**	0.039***	0.006	0.025***
(in logs)	(0.010)	(0.010)	(0.011)	(0.012)	(0.004)
D (no investment)	-0.243***	-0.152***	-0.197***	-0.152***	0.019
	(0.035)	(0.036)	(0.040)	(0.044)	(0.025)
Log employment	0.232***	0.276***	0.251***	0.253***	0.103***
	(0.016)	(0.016)	(0.017)	(0.019)	(0.006)
Log employment squared	-0.035***	-0.052***	-0.054***	-0.052***	-0.023***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.003)
Log age	0.011	0.069***	0.032*	0.041*	0.012*
	(0.018)	(0.019)	(0.019)	(0.022)	(0.007)
Log age squared	0.003	-0.012	-0.030	-0.032	-0.004
	(0.017)	(0.018)	(0.019)	(0.020)	(0.006)
Employees at max (s.e.)					437 (87)***
Age at maximum (s.e.)					256 (230)
Number of observations	14294				14294
Pseudo R-squared					0.102
Log likelihood	-27,382.89				-8,120.47

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

Table 5 - Labor productivity equation

Dependent variable	Labor productivity Log (net sales per employee)			
Dummy for any innovation		-0.002		
		(0.012)		
Predicted probability of any innovation			0.191***	-0.026
			(0.056)	(0.071)
Predicted R&D intensity (in logs)	0.106***			
	(0.020)			
ICT inv. per employee (in logs)	0.089***			0.095***
	(0.005)			(0.006)
D (no ICT investment)	-0.116***			-0.118***
	(0.014)			(0.018)
Investment per employee (in logs)	0.010*			
	(0.006)			
D (no investment)	0.177***			
	(0.039)			
Log (capital per employee)	0.141***	0.159***	0.153***	0.144***
	(0.007)	(0.006)	(0.006)	(0.006)
Log employment	-0.061***	-0.087***	-0.102***	-0.080***
	(0.009)	(0.009)	(0.010)	(0.010)
Log employment squared	0.029***	0.039***	0.042***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Log age	-0.022**	-0.028***	0.028***	0.029***
	(0.010)	(0.010)	(0.010)	(0.010)
Log age squared	-0.007	-0.005	-0.005	-0.006
	(0.009)	(0.009)	(0.009)	(0.009)
Employees at minimum (s.e.)	134 (16)***	143 (13)***	160 (15)***	142 (14)***
Standard error	0.597	0.607	0.606	0.599
R-squared	0.260	0.236	0.237	0.255
Number of observations	14294	14294	14294	14294

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.
* = significant at 10%, ** = significant at 5%, *** = significant at 1% .

Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.

Table 6 - Results of complementarity of different kinds of innovation tests using four equation innovation model (process, product, organizational related to process, organizational related to 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
Using Bivariate Model of innovation						
org proc and org prod	0.567	*	1.75	1.323	0.093	0.429
prod and org prod	-1.913	**	4.02	2.005	0.022	0.954
prod and org proc	0.007		0.001	0.032	0.487	0.221
proc and org prod	-0.204		0.17	0.412	0.340	0.495
proc and org proc	-1.500	***	11.45	3.384	0.000	0.443
proc and prod	0.074		0.10	0.316	0.376	0.234
*E.g., the first value is p0011-p0010-p0001+p0000						

Appendix Tables

Table A1 - Industrial distribution of the sample

Sector	*Firms*	*Observations*	*Share nonzero R&D*	*Share nonzero ICT*	*Median R&D per empl.**	*Median ICT per empl.**
Food and beverage	984	1,397	27.8%	64.0%	1291.1	342.5
Textiles & apparel	829	1,215	33.0%	68.0%	1842.6	322.4
Leather & 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 & 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 & plastics	559	818	33.1%	66.6%	1597.4	329.8
Stone, clay, 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	1,217	1,756	26.5%	68.8%	1702.4	309.4
Machinery	1,423	2,142	47.4%	73.1%	1912.8	390.5
Electrical mach & 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	**9,850**	**14,294**	**34.2%**	**68.3%**	**1662.7**	**337.0**

Distribution by year

Year	*Firms starting in year*	*Observations*	*Share nonzero R&D*	*Share nonzero ICT*	*Median R&D per empl.**	*Median ICT per empl.**
1997	4,006	4,006	29.8%	69.0%	1335.7	344.8
2000	2,887	4,065	35.6%	80.8%	1519.0	322.8
2003	1,460	3,451	41.2%	68.5%	1443.9	298.6
2006	1,497	2,772	30.0%	48.9%	3296.1	446.9
Total	**9,850**	**14,294**	**34.2%**	**68.3%**	**1662.7**	**337.0**

* in euros, for firms with nonzero values.

Table A2 - Sample distribution by region and year

									Shares		
Area	*Code*	*Regione*	*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	1,179	1,100	919	848	4,046	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**	**14294**	**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**	**14294**	**34.3%**	**68.3%**	**62.9%**	**28.8%**

Table A3 - R&D equation with selection

	(1)	(2)	(3)	(4)
	Probit	OLS	Sample selection model	
Dependent variable	Prob R&D nonzero	Log R&D per employee	Prob R&D nonzero	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)
Predicted Pr(R&D>0)		85.520		
		(67.495)		
Inverse Mill's ratio		-79.536		
		(83.020)		
Square Predicted Pr(R&D>0)		-128.546		
		(107.739)		
Square Inverse Mill's ratio		8.366		
		(9.860)		
Pred. Pr(R&D>0) * Inverse Mill's ratio		-122.748		
		(102.515)		
Standard error		1.212	1.279*** (0.021)	
Correlation coefficient	0.0		0.416*** (0.042)	
Number of observations (nonzero)	14294 (4896)		14294 (4896)	
Loglikelihood	-8218.99	-7853.68	-16067.6	

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.
* = significant at 10%, ** = significant at 5%, *** = significant at 1% .

Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.

The first, third, and fourth columns show chi-squared tests, and the second shows F-tests.

Table A4 - ICT equation with selection

	(1)	(2)	(3)	(4)
	Probit	OLS	Sample selection model	
Dependent variable	Prob ICT nonzero	Log ICT inv. per employee	Prob ICT nonzero	Log ICT inv. per employee
Log employment	0.197***	-0.126***	0.197***	-0.115***
	(0.016)	(0.019)	(0.016)	(0.020)
Log employment squared	-0.058***	0.045***	-0.058***	0.042***
	(0.007)	(0.009)	(0.007)	(0.008)
Log age	0.040**	0.031	0.040**	0.033
	(0.019)	(0.021)	(0.019)	(0.020)
Log age squared	-0.012	0.007	0.012	0.008
	(0.018)	(0.020)	(0.018)	(0.020)
D(Large firm competitors)	0.050**	0.014	0.050**	0.016
	(0.025)	(0.027)	(0.025)	(0.027)
D(Regional competitors)	0.124***	-0.080	0.124***	-0.073
	(0.044)	(0.057)	(0.044)	(0.053)
D(National competitors)	0.178***	-0.007	0.178***	0.003
	(0.039)	(0.050)	(0.039)	(0.047)
D(European competitors)	0.309***	0.067	0.310***	0.084
	(0.046)	(0.056)	(0.046)	(0.054)
D(International competitors)	0.331***	0.086	0.332***	0.103*
	(0.048)	(0.058)	(0.048)	(0.057)
D(Received subsidies)	0.227***	0.089***	0.227***	0.100***
	(0.027)	(0.027)	(0.027)	(0.030)
D(Member of a group)	-0.015	0.239***	-0.014	0.238***
	(0.031)	(0.035)	(0.031)	(0.033)
Predicted Pr(R&D>0)		303.413**		
		(149.211)		
Inverse Mill's ratio		175.958***		
		(65.405)		
Square Predicted Pr(R&D>0)		-150.299*		
		(91.655)		
Square Inverse Mill's ratio		-47.890**		
		(19.503)		
Pred. Pr(R&D>0) * Inverse Mill's ratio		-168.224*		
		(94.274)		
Standard error		1.237	1.235*** (0.010)	
Correlation coefficient	0.0		0.090 (0.079)	
Number of observations (nonzero)	14294 (9768)		14294 (9768)	
Log likelihood	-8146.61	-15900.80	-24046.7	

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.
* = significant at 10%, ** = significant at 5%, *** = significant at 1% .

Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.
The first, third, and fourth columns show chi-squared tests, and the second shows F-tests.

Table A5 - Correlation of innovation variables

	Process innovation	Product innovation	Process-related org change	Product-related org change
	Actual			
Process innovation	1.000			
Product innovation	0.292	1.000		
Process-related org change	0.346	0.128	1.000	
Product-related org change	0.163	0.412	0.433	1.000
	*Predicted probabilities**			
Process innovation	1.000			
Product innovation	0.396	1.000		
Process-related org change	0.674	0.285	1.000	
Product-related org change	0.446	0.859	0.544	1.000
	*Estimated correlation of the disturbances**			
Process innovation	1.000			
Product innovation	0.449	1.000		
Process-related org change	0.551	0.183	1.000	
Product-related org change	0.295	0.624	0.639	1.000

*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 with respect to productivity

Dependent variable	Bivariate probit R&D	Bivariate probit ICT	Labor productivity R&D and ICT dummies actual	Labor productivity R&D and ICT dummies predicted	Labor productivity R&D and ICT dummies actual	Labor productivity R&D and ICT dummies predicted
R&D investment nonzero			0.073***	1.024***	0.090***	2.532***
			(0.012)	(0.120)	(0.023)	(0.407)
ICT investment nonzero			-0.001	-1.510***	0.005	-1.772***
			(0.012)	(0.190)	(0.014)	(0.201)
Both R&D & ICT nonzero					0.072***	-0.664***
					(0.016)	(0.121)
Log capital per employee			0.157	0.157***	0.157	0.158***
			(0.006)	(0.006)	(0.006)	(0.006)
Log employment	0.232***	0.198***	-0.094***	-0.073***	-0.094***	-0.071***
	(0.016)	(0.016)	(0.009)	(0.012)	(0.009)	(0.012)
Log employment squared	-0.037***	-0.058***	0.040***	0.019***	0.040***	0.012**
	(0.007)	(0.007)	(0.004)	(0.005)	(0.004)	(0.005)
Log age	0.020	0.040**	-0.028***	-0.015*	-0.028***	-0.009
	(0.018)	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)
Log age squared	-0.003	0.012	-0.005	0.003	-0.005	0.004
	(0.018)	(0.018)	(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(Intl competitors)	0.440***	0.332***				
	(0.049)	(0.049)				
D(Received subsidies)	0.309***	0.227***				
	(0.026)	(0.027)				
D(Member of a group)	0.079***	-0.014				
	(0.030)	(0.031)				
Test for complementarity					-0.023	-1.425
					(0.026)	(0.363)
Rho	0.244 (0.015)					
Log likelihood	-16239.9					
Std. error (R-squared)			0.606 (0.238)	0.605 (0.240)	0.606 (0.239)	0.605 (0.241)
Number of obs nonzero	4,896	9,678	14,294	14,294	14,294	14,294

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.
* = significant at 10%, ** = significant at 5%, *** = significant at 1% .

Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.

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

Dependent variable	Probit									
	Process		Product		Org process		Org product		Any innovation	
	actual	predicted	actual	predicted	actual	predicted	actual	predicted	actual	predicted
R&D investment nonzero	0.478***	0.160	0.740***	1.331	0.357***	2.378***	0.470***	0.726	0.831***	1.749**
	(0.047)	(0.818)	(0.048)	(0.841)	(0.054)	(0.912)	(0.058)	(0.978)	(0.052)	(0.878)
ICT investment nonzero	0.264***	1.682***	0.196***	-0.009	0.348***	1.262***	0.264***	0.446	0.303***	1.139***
	(0.029)	(0.418)	(0.030)	(0.432)	(0.034)	(0.468)	(0.040)	(0.533)	(0.028)	(0.430)
Both R&D & ICT nonzero	0.758***	2.612***	0.943***	2.360***	0.717***	2.558***	0.795***	2.330***	1.153***	3.073***
	(0.033)	(0.255)	(0.034)	(0.261)	(0.036)	(0.282)	(0.042)	(0.319)	(0.036)	(0.264)
Log employment	0.144***	-0.009	0.142***	-0.008	0.160***	-0.013	0.142***	-0.012	0.159***	-0.031
	(0.014)	(0.022)	(0.015)	(0.022)	(0.016)	(0.024)	(0.018)	(0.027)	(0.015)	(0.023)
Log employment squared	-0.004	0.031***	-0.012*	0.005	-0.021***	0.006	-0.011	0.012	-0.020***	0.011
	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.011)	(0.008)	(0.012)	(0.007)	(0.010)
Log age	-0.022	-0.048***	0.030*	0.016	-0.004	-0.022	0.018	0.000	-0.009	-0.031
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.020)	(0.022)	(0.022)	(0.019)	(0.019)
Log age squared	0.011	0.004	-0.006	-0.008	-0.024	-0.025	-0.034	-0.038*	-0.001	-0.005
	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)	(0.019)	(0.022)	(0.021)	(0.018)	(0.018)
Test for complementarity	0.016	0.769	0.007	1.038	0.012	-1.081	0.061	1.157	0.018	0.185
	(0.054)	(0.736)	(0.055)	(0.753)	(0.060)	(0.831)	(0.066)	(0.875)	(0.061)	(0.795)
Log likelihood	-8985.4	-9191.3	-8298.1	-8699.1	-7335.1	-7447.3	-5477.4	-5630.4	-7868.1	-8339.8
Pseudo R-squared	0.122	0.096	0.168	0.112	0.075	0.059	0.081	0.058	0.154	0.096
Number of observations	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294	14,294

Coefficients and their standard errors are shown. The standard errors are robust to heteroskedasticity and clustered at the firm level.

* = significant at 10%, ** = significant at 5%, *** = significant at 1% .

Industry, wave, regional, and time dummies are included in all equations.
Reference groups: D(provincial competitors), Lombardia, 1997, first wave pattern.