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Productivity, Innovation Creation and Absorption, and R&D: Micro Evidence for Italy

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Abstract

By exploiting a rich firm-level database, this paper presents novel empirical evidence on the effect of process and product innovations on productivity, as well as on the role played by R&D and fixed capital investment in enhancing the likelihood of introducing innovations at the firm level. Our results imply that process innovation has a large impact on productivity. Furthermore, R&D spending is strongly positively associated with the probability of introducing a new product, whereas fixed capital spending increases the likelihood of introducing a process innovation. The latter result reflects the fact that new technologies are frequently embodied in new capital goods. However, the effect of fixed investment on the probability of introducing a process innovation is magnified by R&D spending internal to the firm. This implies that R&D affects productivity growth by facilitating the absorption of new technologies.

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1 Introduction

What is the effect of innovations on productivity? How is the introduction of innovations related to R&D? Does R&D only stimulate the creation of innovations, or does it also help the firm in absorbing new technology created by others? Do the answers differ for product versus process innovations? All these are fundamental questions that one would like to have an answer for. We try to provide one in this paper, using very rich panel data for Italian firms collected by Mediocredito Centrale. This data set complements standard balance sheet data with the information from two surveys taken in 1998 and 1995. Among other things, the latter contain information on the inputs and outputs of firm's innovative activities, including whether firms have introduced process or product innovations over the three years preceding each survey.

Using these data, we can estimate directly the effect of the various types of innovations on productivity, without relying on input measures of the innovation process, such as formal R&D expenditure, or on partial and indirect output measures, such as patents. Moreover we can also address the separate question concerning the effect of R&D expenditure on the probability of introducing new processes or products and how R&D interacts with different ways of generating process innovations, such as purchasing new machines that embody a new technology.

Our paper contributes to the empirical literature that has tried to measure the impact of innovation on productivity using aggregate, industry or firm level data. The standard approach has been to estimate the output elasticity of the R&D stock and the rate of return to R&D investment typically by using a Cobb-Douglas production function that includes the R&D capital stock as a separable factor of production.[1] We depart from it by explicitly taking into account that it is innovation output and not innovation input that directly affects productivity growth. Obviously R&D has still a crucial role to play since it is an important factor, but not necessarily the only one, that affects the development and introduction of product or process innovations.

Our decomposition of the R&D productivity link in two separate parts is similar in spirit to Crepon, Duguet and Mairesse (1998) who use patents and the share of sales accounted for by new products as a measure of the output of the innovation process, and include these variables in the production function.[2] An important advantage of the data set we use is that we have two repeated pieces of information on innovations and six years of observations on balance sheet items, while Crepon et al. (1998) must rely on information at a single point in time. This allows us, in principle, to control for firm specific and time invariant components of the error term and to deal with some

[1]Most econometric studies based on aggregate or industry level data report a large, positive and significant effect of R&D on productivity (see, for instance, Guellec and Van Pottelsberghe, 2001, for recent estimates on a panel of OECD countries). The evidence based on firm level data is more mixed. However, recent studies including Lichtenberg and Siegel (1991) on the US, Hall and Mairesse (1995) on France, Mairesse and Hall (1996) on France and the US, Harhoff (1998) on Germany, Klette and Johansen (1998) on Norway, Parisi (2001), ch.2, for Italy confirm the positive sign (but not always the magnitude) found in aggregate studies. See also the contributions in Griliches (1998) for some of the most influential earlier studies.

[2]Their productivity equation is part of a more general model which also includes equations for innovation output and for the R&D decision. See also Mairesse and Mohen (2001) on measurement issues.

of the endogeneity problems. Another distinguishing feature of our paper is the focus both on the creation and absorption of innovations, and on the role of R&D in this respect, both for product and process innovations.

Indeed, simple descriptive statistics suggest that process and product innovation are distinct, in the sense that one of the two activities does not necessarily imply the other. For instance, only approximately half of the firms in our sample that have introduced a process innovation also introduce a product innovation. In our econometric work, we find a positive, statistically significant and sizeable effect of innovation on productivity, when we include a dummy, representing whether an innovation has been introduced or not, in a standard Cobb Douglas production function, As one would expect, the productivity effect of a process innovation is larger than the one of a product innovation. Actually, when both innovation dummies are included together in the equation, the product innovation dummy is dominated by the process innovation dummy.

Moreover, there are intriguing differences in the way in which R&D spending is related to the probability of introducing product versus process innovation. R&D spending is strongly directly associated with the introduction of a new product, but it is not a necessary condition for the introduction of a new process. The latter is strongly associated with spending on new fixed capital, suggesting an important role for embodied technological progress. However the effect of investment spending on new machines on the probability of introducing a process innovation is enhanced by R&D spending. This implies that there may be an important role for R&D in favoring the absorption of new more advanced technologies. Once they have been introduced, however, R&D does not significantly affect their effective use. The effect of R&D on growth through its effect on facilitating the absorption and transfer of new technologies have been analyzed for OECD countries by Griffith, Redding and Van Reenen (2001) and by Guellec and Van Pottelsberghe (2001). Our results provide interesting micro based support for the importance of the technology absorption effect of R&D at the firm level.

The investigation of all these topics poses difficult econometric challenges. In estimating the production function one should address the issue of firm specific and time invariant components of the error term. Moreover, the idiosyncratic component of the error term may represent stochastic shocks to technology that are correlated both with the introduction of innovations and with the choice of capital, labor and material inputs. Finally there is the issue of measurement errors in the regressors. We are going to address these issues by estimating the production function in long differences (between 1997 and 1994) and by using variables dated 1993 and earlier as instruments. Similar problems arise in the context of the probability model for the introduction of innovations. Compared to the case of the production function, there is no way of addressing all legitimate concerns simultaneously, since only two time periods are available for the dependent variables. We will present a menu of estimators that address particular aspects of the problem and discuss their advantages and disadvantages.

The paper is organized as follows. In section 2 we describe the data set we use for our investigation. In Section 3 we present the main econometric results on the effects of innovation on productivity, based on the estimation of a standard Cobb Douglas production function, augmented by our innovation dummies. In section 4 we study the determinants of the probability of introducing an innovation. Section 5 concludes the paper.

2 Data and Descriptive Statistics on R&D and Innovations

The data come from the 6th and 7th surveys "Indagine sulle Imprese Manifatturiere" by Mediocredito Centrale, MCC from now on.[3] These are two surveys conducted in 1995 and 1998 through questionnaires administered to a representative sample of manufacturing firms within the national borders and supplemented with standard balance sheet data. In each wave the sample is selected with a stratified method for firms with up to 500 workers, whereas firms above this threshold are all included. Strata are based on geographical area, industry and firm size. Each survey contains about 5000 manufacturing firms. Questionnaires collect information over the previous three years (1994-1992 and 1997-1995). We merged the two MCC's samples and obtained

[3] The surveys are run by the "Osservatorio sulle Piccole e Medie Imprese" (*Observatory over SMEs)*, an institution associated with Mediocredito Centrale, an Italian investment bank. More detailed information about the surveys is found in the Mediocredito Centrale publications (see for example Ministero dell' Industria - Mediocredito Centrale, 1997) and its web site www.mcc.it.

a reduced sample of 941 firms, keeping only those firms answering to both questionnaires and therefore with potentially complete observations over the 1992-1997 period. We further excluded from the sample firms with incomplete information or with extreme observations for the variables of interest. Details of the sample selection procedures are contained in Appendix 1. The final sample contains 465 firms.

Table 1 reports means (and standard deviations) for the regressors that will enter our productivity equation together with a set of dummies proxying for technological change. In particular $\ln(Y_t/L_{t-1})$, $\ln(M_t/L_{t-1})$, $\ln(K_t/L_t)$ denote respectively the (log of the) output, material, and capital to labor ratios. Y_t represents total gross output, measured as sales plus inventory accumulation of finished and intermediate goods. M_t is a Tornquist index of material and services used. K_t measures the fixed capital stock and is constructed with the perpetual inventory method, starting from the capital stock in the first year at historical cost, revalued for inflation. L_t includes all employees, except those involved in R&D with the purpose of avoiding double counting. Exact variable definitions are contained in Appendix 2.

Table 2 reports the mean (and standard deviation) for different measures of R&D intensity, expressed as a percentage of production, P_t, or of the total capital stock (fixed capital plus R&D capital), TK_t.[4] For comparison, measures of intensity of investment in fixed capital are also reported. The R&D intensity measures are computed both for the total sample of firms and

[4]Details on the construction of the R&D capital stock are contained in Appendix 2. See also Parisi (2001), appendices to ch.2.

for those that are engaged in formal R&D activities. The most important information contained in Table 2 is the large percentage of firms characterized by zero formal R&D activity. For instance, R&D equals zero in 49.3% of the observations during the period 1992-94 and in 56.1% in the 1995-97 period. Furthermore, this happens to be the case not only if we simply count the number of firm-year observations with zero R&D flow ($R\&D = 0$), but also if we make use of two alternative and less restrictive measures which respectively count the number of firm-year observations with zero R&D capital stock ($R\&D\ \ stock = 0$) and the number of firms which declare not to have invested in R&D in any year of the relevant wave ($R\&D\ \ average = 0$).

This descriptive micro evidence is hardly surprising and confirms the low R&D intensity of the Italian economy that can be observed in aggregate statistics.[5] For instance, business R&D statistics published yearly by the OECD suggest that in Italy, business R&D spending relative to value added was on average only 0.7% in the period 1995-99, compared to 1.5% average figure for the EU and 1.8% for the OECD countries (OECD, 2001, Table A.4.1.2). Formal R&D spending in the OECD is heavily concentrated in high or medium-high technology industries (representing 52.2% and 35.5%, respectively, of total R&D spending in OECD countries), and it is mainly carried out by firms with more than 500 employees (74.8% in the UK, 78.9% in France, and 81.4% in Germany, just to mention countries of comparable size and GDP per capita). The specialization of Italian firms in low-medium

[5] See also Malerba (1993) for a general discussion.

technology industries (Malaman, 1997) and the within industry abnormally low size of Italian firms (Nicoletti, 2002) play an important role in explaining the low R&D intensity reported in official statistics and confirmed by our micro evidence. It is possible that statistics on formal R&D spending misrepresent the "true" innovative effort carried out at the firm level, particularly for small firms that are more likely to be engaged in informal or "tacit" R&D activities. Still, the high frequency of absence of R&D activity revealed by MCC panel should be a cause for concern.[6]

Table 3 summarizes additional information about the introduction of innovations by our sample of Italian firms and about the nature of the innovations. The first four rows report, separately for each wave, the probabilities of introducing a process innovation, a product innovation, either a process or a product innovation, both a process and a product innovation. In the next two rows, the probability of introducing a product (process) innovation is instead calculated conditional to having introduced a process (product) innovation. Two main comments are worth making at this stage. First, process innovation is more frequent than product innovation. In fact, only around half of the firms declare to have introduced at least one product innovation in three years and this figure increases somewhat between the 1992-94 and 1995-97 period (from 49.5% to 54.6%). The share of firms introducing process innovation is instead far higher, since around two thirds or more of the firms declare to have introduced process innovations (66.0% in 1992-94 and

[6] On this issue see Archibugi and Ceccagnoli (1995).

69.5% in 1995-97). Second, the probability of introducing a product innovation is higher for firms that have also introduced a process innovation in the same time period. This is not surprising since the introduction of a new product may well require a new production technique or at least the updating of an existing one. However, process innovation does not necessarily imply product innovation. In fact, conditional on having introduced a new process, only 56.4% (62.2%) of firms introduce a new product in 1992-94 (1995-97).

Finally, the last two rows report the probabilities of introducing a product (process) innovation conditional on performing R&D activity. As it can be seen, the conditional probabilities are higher than the corresponding unconditional probabilities for both types of innovations. This suggests that R&D spending is positively correlated with both types of innovation. However, the share of firms introducing a process innovation (66.0% in 1992-94 and 69.5% in 1995-97) is higher than the share of firms engaged in at least some R&D activity (53.3% in 1992-94 and 46.0% in 1995-97, see Table 2). This suggests that there are other determinants of the probability of introducing a new process, besides the own R&D conducted by the firm. For instance, new technologies may be embodied in the new capital goods purchased by the firm, in which case the firm avails itself of the technological improvements achieved in the domestic or foreign investment goods sectors. A crucial question is whether R&D conducted internally to the firm facilitates the absorption of new technology. Some amount of internal R&D may be useful in identifying the blue prints embodied in new capital goods that represent the technological frontier, in adapting them to the firm needs, and installing them. We will address this issue later in section 4.

3 Estimating the Effect of Innovations on Productivity

In order to assess the effect of innovation on productivity we estimate a Cobb-Douglas production function in long differences, augmented with the innovation dummies. More specifically, denoting materials with M, capital with K, and labor with L, we can write:

$$\ln Y_{it} = \ln A_{it} + \theta \ln M_{it} + \beta \ln K_{it-1} + \alpha \ln L_{it-1} + \lambda_i + \varepsilon_{it} + \eta_t \qquad (1)$$

A_{it} represent the state of technology. The indexes i and t denote firms and time, respectively. $\lambda_i, \varepsilon_{it}$, and η_t represent, in turn, a firm specific, idiosyncratic and common stochastic shocks. Denote with D_{itj} a dummy that equals one if firm i says that an innovation of type j has been introduced in the three years ending at t, and is zero otherwise. j denotes either process innovations, product innovations, or the union of the two. We capture the effect of technological progress on productivity using these dummies. More specifically, in the basic specification, we assume that the rate of technological progress can be written as:

$$\Delta \ln A_{it} = \phi + \psi D_{itj} \tag{2}$$

Using (2) into (1), assuming constant returns to scale, and taking differences we obtain:

$$\Delta_3 \ln \frac{Y_{it}}{L_{it-1}} = \phi + \psi D_{itj} + \theta \Delta_3 \ln \frac{M_{it}}{L_{it-1}} + \beta \Delta_3 \ln \frac{K_{it-1}}{L_{it-1}} + \Delta_3 \varepsilon_{it} + \Delta_3 \eta_t \tag{3}$$

Variables are long differences (Δ_3 denotes differences between t and $t-3$) to capture the effect of introducing an innovation in the 1995-97 period on the change in productivity between 1997 and 1994, which we consider a plausible time span to observe an effect.[7] We apply Instrumental Variables to equation (3), using variables dated 1993 or 1992 as instruments. This choice is legitimate if $\{\varepsilon_{it}\}$ is a white noise or a random walk stochastic process. However, the set of instruments is not valid if $\{\varepsilon_{it}\}$ is an $AR(1)$ process. Since our model is estimated with a single cross-section, standard tests on the presence of first and second-order serial correlation cannot be computed. However, we present the Sargan-Hansen test of overidentyfing restrictions whose rejection can be interpreted as evidence against the validity of some of the instruments.

In Tables 4 and 5 we report the main results of estimating equation (3).

[7] Long differences are often used to get rid of potential sources of bias such as "survey" effects, "firm" specific effects, and to average out measurement errors (Harhoff, 1998).

We can never reject the constant return to scale assumption. The two tables differ only because in the former the lagged value of output per worker is included in the instrument set, while in the latter it is excluded. A complete list of instruments can be found in the notes at the bottom of each table. The coefficient of the Tornquist index for materials and services per worker has a significant coefficient around 0.7 in all specifications, which is reasonable. The magnitude of the capital to labor coefficient also is what one would expect on the basis of income shares, suggesting that capital receives approximately 1/3 of what is left after accounting for the use of materials. However it is never significant.

Let us concentrate now on the effect of innovations. In the first column of Table 4, the innovation dummy represents whether either a process or product innovation has been introduced. It is obvious why process innovation can increase productivity. It is also possible that the introduction of a new product allows a reorganization and simplification of the production process that may not be identified as a process innovation by the firm. The coefficient of the dummy is significant at the 5% level. In column 2 we include the process innovation dummy and the product innovation dummy at the same time The coefficient of the process innovation dummy is significant at the 10% level, while the one of the product innovation dummy is not. The effect of a process innovation is sizeable and it leads to an increase of productivity of 15%. In column 3 only the process dummy is included whereas in column 4 only the product dummy is included. Again we obtain the result that the coefficient for the process innovation dummy is significant, at the 5% level, while the one for product innovation is not.[8] Note that the size of the capital coefficient in the specification with the product dummy only, not only is insignificant, but it is also unreasonably small. Note that the R^2 in all specifications is quite respectable (above 50%) and that the Sargan-Hansen test does not reject the validity of the instruments. The results in Table 5 are similar, The only substantial difference is that now also the product innovation dummy is significant, when it is included alone in the equation. However, its coefficient remains smaller than the one for process innovation (0.11 versus 0.16). Also the Sargan-Hansen test is characterized by larger marginal probabilities in column 4 of Table 5 (0.17) compared to its counterpart in Table 4 (0.48).

One obvious criticism to the results presented so far is that the effect of an innovation on productivity has been imposed to be the same, independently of the size of the firm and of the sector in which it operates. To address this legitimate concern, we also estimated two additional sets of equations where the coefficients on the innovation dummies are allowed to vary by size (Small versus Medium-Large firms) and by industry (High-Tech versus Low-Tech industries) respectively. Operationally, this has been done by adding to (3)

[8] Klette and Griliches (1996) have emphasized the difficulty of obtaining consistent estimates of production function parameters when firms operate in an imperfectly competitive envronment and only the average price level is observed. In these circumstances, if a firm that introduces a process innovation lowers its relative product price, one may underestimate the productivity growth that results from process innovation. If this is the case, one may consider our estimate a lower bound of the true effect of process innovation. If product innovation, leads to an increase in the firm relative output price, the effect of product inovation is, instead, overestimated.

an additional set of variables obtained by interacting the innovation dummies with a dummy which is equal to 1 if a firm is medium-large (ML) and zero otherwise or with a dummy which is equal to 1 if a firm operates in a High-Tech industry (HT) and zero otherwise.[9] In Table 4 and 5 Wald tests on the joint significance of these interactions are reported. The null hypothesis of equality of coefficients is never rejected at the usual confidence levels with the only exception of the size dummy in the equation where technical change is proxied by the product innovation dummy (column 4 in Tables 4 and 5). Here the size on the interaction term points out that the effect of a product innovation is positive and significant for the sub-sample of medium-large firms.[10]

Finally, it is possible that the quality and productivity enhancing effects of each innovation generated within the firm may be related to internal R&D intensity. Alternatively, it may be the case that, once introduced, the effective use of a process innovation acquired from outside the firm depends upon the amount of internal R&D activity. Both arguments suggest that the coefficient of our innovation dummy could depend upon measures of R&D intensity. We have therefore interacted the innovation dummies with R&D spending as a proportion of total capital, R&D capital as a proportion of total capital, and R&D workers as a proportion of total workers. Even if positive, in no case was the coefficient of the interaction term significant. Therefore, we find no

[9] A detailed description of the criteria used to build our two dummy variables can be found in Appendix 1.

[10] These additional equations are available upon request from the authors.

empirical support for the plausible hypothesis that internal R&D increases the effective use of an innovation or its quality.

4 R&D, Investment and Innovations

What is the role of R&D in stimulating the creation of innovations within the firm? What is its role in making possible and facilitating the absorption of innovations embodied in capital goods purchased by the firm? All these are very important questions that need to be addressed. In this section we will present some evidence that, while not conclusive, starts shedding some light on these issues for our sample of firms.

We will estimate a menu of probability models for the introduction of a product or a process innovation as a function of size (measured by the log of the total capital stock at the beginning of each sub-period), average R&D intensity, measured as R&D spending divided by total capital, and average fixed investment intensity (also relative to total capital) in each sub-period, the interaction between the two, and other firm characteristics, such as age, group membership, industry and geographical location.

The results are reported in Table 6 for product innovation and in Table 7 for process innovation. We present logit results with and without random effects as well as conditional logit results. One fundamental problem here is to control for unobserved firm characteristics that are relatively constant through time. Simple logit models assume the problem away. Random effects logit models allow for unobservable characteristics, but require, in order to get consistent results, that they are independent from the other explanatory variables, which is an unlikely event. Conditional logit models eliminate the firm specific effects, but only switchers (firms that introduce an innovation in just one of the sub-periods) contribute to the likelihood function. Another problem is that endogeneity can arise not only because of the presence of a firm effect (an issue that we try to address by presenting conditional logit estimates) but also because there is a shock to the technological frontier (say a new invention, technological breakthrough, etc.) that leads to an increase both in the probability of observing an innovation and on research and investment intensity. This is reflected in the idiosyncratic component of the error term. Ideally, to control for this additional source of endogeneity we would need observations for at least three points in time ($t = 3$). Unfortunately we cannot address this problem with our data-set since the qualitative information on innovation reported in each survey are not available on a yearly basis, but on a (3 years) period basis.

The probability of introducing a product innovation is found to increase significantly with firm size, as one would expect. The only exception are the conditional logit results, in which case the coefficient on total capital is large but very imprecisely estimated (see Table 6).[11] More importantly for the purpose of this paper, R&D intensity is positively, significantly and strongly directly associated with the introduction of product innovations. This is

[11] This is not surprising since the capital stock is a slowly evolving variable for many firms.

true at the 5% level in all the models, again with the exception of the conditional logit model, where the R&D intensity coefficient is significant only at the 10% level. This should not be too surprising, since only 37.4% of our sample is made up by switchers and this is likely to reduce the precision of our estimates. Note, however, that its magnitude is identical to the one it has in the simple logit model (0.18) and only slightly lower than the one it has after controlling for the presence of random effects (0.21). Furthermore, the direct effect of investment intensity is also positive but significant, at best, only at the 10% level and not significant in the Conditional Logit model. In none of the cases, the interaction effect between R&D and fixed investment intensity is significantly different from zero. What do these estimates say about the magnitude of the effect of R&D in enhancing the probability of product innovation? Simple calculations show that an increase in R&D intensity from zero to the sample average (1.16%) increases the likelihood of introducing a product innovation approximately by 5.19 percentage points in the simple logit specification and by as much as 6.03 percentage points in the specification with random effects.

For process innovation the story is very different (see Table 7). As for product innovation, the probability of introducing a process innovation is also found to increase with size, with the usual exception of the conditional logit model. The coefficient on investment intensity is significant at the 5% level in the simple and in the random effect logit model, and at 10% in the Conditional Logit model. In addition its size is also very stable across models, ranging from 0.05 to 0.06. This is a piece of evidence consistent with the idea that technological innovations find their way into the firm embodied in new capital goods. On the contrary, the coefficient of R&D intensity is never significant in any of the specifications. However, and this is very interesting, the coefficient of the interaction term between R&D and Investment is significant at the 5% level in the simple and in the Random Effect Logit specifications. This provides support to the idea that internal formal R&D is helpful in allowing firms to absorb new technologies: internal R&D may make it easier to identify the frontier blueprints embodied in new capital goods and in introducing them in the production process.[12]

Note that the results we have described so far are robust to using R&D capital relative to total capital as a measure of R&D intensity. In this case as well R&D has a significant direct effect on the probability of introducing a product innovation and an indirect one on the probability of introducing a process innovation, through the interaction with new investment.[13] If we use instead the percentage of R&D workers out of the total we obtain very imprecise and statistically not significant R&D effects. Possibly this suggests that this latter measure is a poorer proxy for the amount of R&D activity that takes place within the firm.

[12] The importance of embodied technological progress for growth is emphasized in Solow (1960) and discussed in Jorgenson (1966). For recent estimates of the rate of technological change embodied in fixed capital and its contribution to growth see Hulten (1992), Greenwood et al. (1997), Hobijn (1999), and Sakellaris (2001).

[13] For instance, the coefficient on R&D is 0.044 with a t of 2.11 in the random effect logit model for product innovation, while the coefficient of the interaction term with fixed capital investment in the random effect logit model for process innovation is 0.008 with a t of 2.42 .

The role of R&D in enhancing what has been called the "absorptive capacity" of an economy, in addition to its role in stimulating innovation, has been emphasized by many authors.[14] This issue has been analyzed empirically at a more aggregate level. For instance Griffith, Redding and Van Reenen (2000) provide evidence at the industry level for OECD countries that R&D increases TFP growth, both directly, and by enhancing technology transfers from countries at the technology frontier. In the same vein, Guellec and Van Pottelsberghe (2001) show, using aggregate OECD data, that the positive effect of foreign R&D on productivity growth is enhanced by R&D conducted domestically by the business sector. Our results emphasize that the concept of absorptive capacity is important not only at the country or industry level, but also at the firm level: internal R&D helps the firm in absorbing innovations generated outside the firm and embodied in new investment goods. These innovations, in turn, increase the firm's productivity.

In order to assess the quantitative importance of these effects, we have performed a very simple experiment. We have computed the (approximate) impact on the likelihood of introducing a process innovation of an increase in fixed capital investment from zero to its sample mean (7.27%), conditional respectively on not doing R&D research and on having an average R&D intensity (1.17%). The difference between these two probabilities can be taken as a rough measure of R&D investment in facilitating the absorption

[14] See, for instance, Rosenberg (1982), Cohen and Levinthal (1989), Romer (1990), Grossman and Helpman (1991), Segestrom (1991), Neary and Leahy (1999), and Griffith, Redding and Van Reenen (2000).

of new technology. In the first scenario (no R&D investor) the likelihood increases by 8.10 percentage points in the simple logit model (and by 8.22 percentage points in the random effect logit model). In the second scenario (at average R&D intensity) the effect is stronger. In fact, for the average R&D intensity, the likelihood of introducing a process innovation increases by 12.65 percentage points in the simple logit and by 12.77 percentage points in the random effect model. There is therefore a sizeable increase of 4.55 percentage points in the probability of introducing a process innovation when a firm does internal R&D. These results, however, are not robust to the accounting for the presence of fixed effects, as it is done in the conditional logit model. Again the loss of information due to having to rely only on the switchers may explain this result.

Finally, as in the previous section, we also estimated two additional sets of equations where the coefficients on R&D intensity, fixed investment intensity and its interaction are allowed to vary by size and by type of industry (high tech or not). In Table 6 and 7, Wald tests on the joint significance of these interactions are reported. Our overall results are found to be very stable across firm size and type of industry, since the null hypothesis is never rejected at the usual confidence levels with the only exception of the HT dummy in the Conditional Logit Model for product innovation.[15]

[15] These additional equations are available upon request from the authors.

5 Conclusions

In this paper we have provided panel data evidence on the pattern of innovation activity for a large sample of Italian firms and on its effect on productivity. Using a discrete measure of innovation output, we find that the introduction of process innovation has a sizeable effect on productivity. As one would expect, the productivity effect of a process innovation is larger than the one of a product innovation.

Moreover, there are very interesting differences in the way in which R&D spending is related to the probability of introducing product versus process innovation. R&D spending is strongly positively associated with the probability of introducing a new product, but not with the probability of introducing a new process. The latter is strongly associated with spending on new fixed capital, suggesting an important role for embodied technological progress. However the effect of investment spending on new machines on the probability of introducing a process innovation is enhanced by R&D spending. This implies that there is an important role for R&D in favoring the absorption of new more advanced technologies. The role of R&D in increasing "absorptive capacity" had been emphasized and documented previously at the country or industry level. We have provided evidence that, also at the firm level, the ability to introduce new technologies generated outside the firm increases with internal R&D spending.

Given our firm level evidence on the important role of R&D in stimulating product innovation and in facilitating the absorption of new technologies that enhance productivity, it is very worrying that Italy is characterized by low business R&D intensity relative to other OECD countries, as emphasized by many researchers. This micro level evidence provides an additional reason, besides country level evidence on the positive role of R&D for growth, why it is imperative to study the structural, institutional and policy reasons for such low R&D activity in Italy.[16]

[16]See, for instance, Nicoletti (2002) for a recent contribution to this debate.

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Table 1: Descriptive Statistics

	Mean	**St. Dev.**	**Min**	**1^{st} decile**	**Median**	**9^{th} decile**	**Max**
$ln\frac{Y_{97}}{L_{96}}$	5.56	0.511	4.23	4.91	5.55	6.20	7.02
$ln\frac{Y_{94}}{L_{93}}$	5.49	0.523	4.22	4.83	5.47	6.18	7.01
$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	0.07	0.233	-0.68	-0.22	0.07	0.36	0.77
$ln\frac{M_{97}}{L_{96}}$	4.64	0.707	2.60	3.76	4.62	5.57	6.32
$ln\frac{M_{94}}{L_{93}}$	4.56	0.741	2.67	3.66	4.51	5.54	6.59
$\Delta_3 ln\frac{M_{97}}{L_{96}}$	0.07	0.274	-1.03	-0.25	0.06	0.43	1.18
$ln\frac{K_{96}}{L_{96}}$	4.66	0.674	2.67	3.79	4.73	5.46	6.26
$ln\frac{K_{93}}{L_{93}}$	4.60	0.664	2.60	3.66	4.67	5.42	6.13
$\Delta_3 ln\frac{K_{96}}{L_{96}}$	0.06	0.211	-0.57	-0.21	0.05	0.32	0.81

Note: Number of firms equals 465. Δ_3 denotes three-year (long) differences. Y_t is production, L_t is non-R&D labor force, K_t is fixed capital, and M_t is materials plus services.

Table 2: Descriptive Statistics (mean and standard deviation)

	1992-94	**1995-97**
Number of Observations	1395	1395
Fixed investment intensity (Y)	3.72 (3.260)	4.11 (3.629)
R&D intensity (Y)	0.59 (0.980)	0.38 (0.816)
Fixed investment intensity (TK)	6.61 (4.360)	7.93 (5.232)
R&D intensity (TK)	1.33 (2.430)	1.01 (2.202)
Share of Observations (R&D $>$ 0)	50.7%	43.9%
R&D intensity (Y) $\mid$ R&D $>$ 0	1.14 (1.123)	0.86 (1.051)
R&D intensity (TK) $\mid$ R&D $>$ 0	2.58 (2.896)	2.25 (2.852)
Share of Observations (R&D stock $>$ 0)	51.8%	62.9%
R&D intensity (Y) $\mid$ R&D stock $>$ 0	1.13 (1.116)	0.61 (0.962)
R&D intensity (TK) $\mid$ R&D stock $>$ 0	2.55 (2.878)	1.60 (2.602)
Share of Observations (R&D average $>$ 0)	53.3%	46.0%
R&D intensity (Y) $\mid$ R&D average $>$ 0	1.10 (1.110)	0.83 (1.038)
R&D intensity (TK) $\mid$ R&D average $>$ 0	2.49 (2.858)	2.19 (2.822)

Note: Firms are 465. Intensities are investment ratios with respect to production (Y) or to total capital ((TK) = Fixed capital (K) + R&D capital (G)), all averaged over the three-year periods. (R&D $>$ 0) counts all firm-years with R&D expenditure greater than zero. (R&D stock $>$ 0) counts all firm-years with positive R&D capital stock. (R&D average $>$ 0) counts all firms which invested in R&D in at least one year in the observed period.

Table 3: Share of Innovative Firms by Type of Innovation (%)

	1992-94	**1995-97**
Process	66.02	69.46
Product	49.46	54.62
Process or Product	78.28	80.85
Process and Product	37.20	43.23
Process $\mid$ Product	75.21	79.15
Product $\mid$ Process	56.35	62.24
Process $\mid$ R&D average > 0	77.82	83.64
Product $\mid$ R&D average > 0	62.50	66.82

Note: the last four rows refer to conditional frequencies.

Table 4: Productivity equations (lagged productivity among instruments)

Number of firms	465	465	465	465
Estimation method	IV	IV	IV	IV
Dependent var.	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$
$\Delta_3 ln\frac{M_{97}}{L_{96}}$	0.69** (0.079)	0.72** (0.082)	0.72** (0.081)	0.71** (0.073)
$\Delta_3 ln\frac{K_{96}}{L_{96}}$	0.07 (0.114)	0.09 (0.129)	0.09 (0.126)	0.01 (0.106)
Either innovations$_{95-97}$	0.16** (0.066)			
Process innovations$_{95-97}$		0.15* (0.084)	0.14** (0.065)	
Product innovations$_{95-97}$		-0.02 (0.076)		0.07 (0.056)
Constant	-0.12** (0.057)	-0.09* (0.051)	-0.09* (0.051)	-0.03 (0.033)
Wald test for *HT	0.10 [0.75]	0.85 [0.43]	0.35 [0.55]	0.19 [0.66]
Wald test for *ML	1.66 [0.20]	0.98 [0.38]	1.28 [0.26]	4.31** [0.04]
R^2	0.57	0.55	0.56	0.59
Sargan test [p-value]	10.48 [0.57]	11.23 [0.42]	11.49 [0.49]	16.62 [0.17]

Note: Robust standard errors in parentheses. *= 10% significance, **= 5% significance for test-statistics. Instruments: $\ln(M_{93}/L_{92})$, $\ln(Y_{93}/L_{92})$, $\ln(K_{92}/L_{92})$, $\ln(K_{93}/L_{93})$, $\ln(K_{92}+G_{92})$, $\ln(K_{93}+G_{93})$, $R\&D_{93}/(K_{93}+G_{93})$, $I_{93}/(K_{93}+G_{93})$, $I_{92}/(K_{92}+G_{92})$, $\ln(L_{92})$, $\ln(L_{93})$, ln(R&D Labor$_{92}$), area dummies. Wald tests test the difference of innovation dummies between High-Tech (HT) and Low-Tech or between Medium-Large (ML) and Small firms. P-values in brackets.

Table 5: Productivity equations (without lagged productivity among instruments)

Number of firms	465	465	465	465
Estimation method	IV	IV	IV	IV
Dependent var.	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$	$\Delta_3 ln\frac{Y_{97}}{L_{96}}$
$\Delta_3 ln\frac{M_{97}}{L_{96}}$	0.70** (0.081)	0.73** (0.082)	0.73** (0.083)	0.72** (0.075)
$\Delta_3 ln\frac{K_{96}}{L_{96}}$	0.09 (0.115)	0.10 (0.130)	0.11 (0.129)	0.02 (0.110)
Either innovations$_{95-97}$	0.18** (0.067)			
Process innovations$_{95-97}$		0.15* (0.085)	0.16** (0.066)	
Product innovations$_{95-97}$		0.02 (0.076)		0.11** (0.056)
Constant	-0.14** (0.058)	-0.11** (0.051)	-0.11** (0.051)	-0.05 (0.033)
Wald test for *HT	0.09 [0.76]	0.38 [0.68]	0.68 [0.41]	0.00 [0.96]
Wald test for *ML	0.85 [0.36]	0.73 [0.48]	0.44 [0.51]	3.40* [0.07]
R^2	0.55	0.54	0.53	0.56
Sargan test [p-value]	5.36 [0.91]	6.60 [0.76]	6.57 [0.83]	10.58 [0.48]

Note: Robust standard errors in parentheses. *= 10% significance, **= 5% significance for test-statistics. Instruments: ln(M_{93}/L_{92}), ln(K_{92}/L_{92}), ln(K_{93}/L_{93}), ln($K_{92}+G_{92}$), ln($K_{93}+G_{93}$), R&D_{93}/($K_{93}+G_{93}$), I_{93}/($K_{93}+G_{93}$), I_{92}/($K_{92}+G_{92}$), ln(L_{92}), ln(L_{93}), ln(R&D Labor$_{92}$), area dummies. Wald tests test the difference of innovation dummies between High-Tech (HT) and Low-Tech or between Medium-Large (ML) and Small firms. P-values in brackets.

Table 6: Product Innovation Equations

Observations	930	930	348
Estimation method	Logit	RE Logit	C Logit
Dependent var.	Product	Product	Product
ln(Fixed+R&D stock)	0.17^{**} (0.063)	0.19^{**} (0.077)	0.56 (0.855)
Investment intensity	0.03^{*} (0.017)	0.04^{*} (0.019)	0.03 (0.028)
∂ Product/∂Investment	0.007^{*} (0.004)	0.009^{*} (0.005)	0.00 (0.001)
R&D intensity	0.18^{**} (0.075)	0.21^{**} (0.070)	0.18^{*} (0.104)
∂ Product/∂R&D	0.04^{**} (0.019)	0.05^{**} (0.017)	0.00 (0.005)
Interaction	-0.00 (0.010)	-0.00 (0.008)	-0.02 (0.011)
∂ Product/∂Interaction	-0.00 (0.003)	-0.00 (0.002)	-0.00 (0.000)
Age	0.00 (0.004)	0.00 (0.005)	
Group membership	-0.14 (0.163)	-0.16 (0.204)	
Constant	-2.28^{**} (0.931)	-2.59 (1.590)	
Wald test [p-value]	22.29^{**} [0.00]	20.32^{**} [0.00]	3.59 [0.31]
Wald test for *HT	3.01 [0.39]	3.59 [0.31]	1.71 [0.64]
Wald test for *ML	4.74 [0.19]	3.72 [0.29]	2.12 [0.55]
Pseudo R^2	0.09		0.02
LR test [p-value]		9.24^{**} [0.00]	
Goodness of fit [p-value]	936.54 [0.21]		
Sensitivity	67.77%		
Positive predictive value	65.60%		
Specificity	61.43%		
Correct classification	64.73%		

Note: Robust standard errors in parentheses. *= 10% significance, **= 5% significance for t-statistics. Fixed Investment and R&D intensities are measured relative to total capital (Fixed+R&D capital stocks). Interaction is the product of fixed investment intensity and R&D intensity. Sector and area dummies are included in Logit and RE Logit models. The first Wald test tests the joint significance of R&D, Investment intensities and their interaction. Additional Wald tests test the difference of coefficients between High-Tech (HT) and Low-Tech firms or between Medium-Large (ML) and Small firms. LR-test tests for no random effects in RE Logit. Goodness of fit is the Pearson chi-square test with 902 dof. P-values in brackets. Sensitivity = $P(\text{positive } outcome \mid Inno = 1)$; Specificity = $P(\text{negative } outcome \mid Inno = 0)$; Positive predictive value = $P(Inno = 1 \mid \text{positive } outcome)$. Correct classification takes all three probabilities into account to evaluate the model.

Table 7: Process Innovation Equations

Observations	930	930	352
Estimation method	Logit	RE Logit	C Logit
Dependent var.	Process	Process	Process
ln(Fixed+R&D stock)	0.41** (0.074)	0.42** (0.074)	-0.10 (0.875)
Investment intensity	0.05** (0.018)	0.06** (0.019)	0.05* (0.031)
∂ Process/∂Investment	0.011** (0.004)	0.011** (0.004)	0.012 (0.027)
R&D intensity	-0.04 (0.073)	-0.04 (0.069)	0.03 (0.098)
∂ Process/∂R&D	-0.008 (0.015)	-0.008 (0.014)	0.006 (0.027)
Interaction	0.03** (0.012)	0.03** (0.012)	0.01 (0.014)
∂ Process/∂Interaction	0.006** (0.003)	0.006** (0.002)	0.002 (0.005)
Age	0.00 (0.004)	0.00 (0.004)	
Group membership	-0.11 (0.181)	-0.11 (0.182)	
Constant	-2.90** (1.257)	-2.94** (1.400)	
Wald test [p-value]	22.54** [0.00]	24.16** (0.00)	4.62 [0.20]
Wald test for *HT	5.03 [0.17]	5.51 [0.14]	9.15** [0.03]
Wald test for *ML	3.95 [0.27]	4.84 [0.18]	1.85 [0.60]
Pseudo R^2	0.10		0.02
LR test [p-value]		0.20 [0.33]	
Goodness of fit [p-value]	936.8 [0.21]		
Sensitivity	90.63%		
Positive predictive value	72.46%		
Specificity	27.67%		
Correct classification	70.32%		

Note: Robust standard errors in parentheses. *= 10% significance, **= 5% significance for t-statistics. Fixed Investment and R&D intensities are measured relative to total capital (Fixed+R&D capital stocks). Interaction is the product of fixed investment intensity and R&D intensity. Sector and area dummies are included in Logit and RE Logit models The first Wald test tests the joint significance of R&D, Investment intensities and their interaction. Additional Wald tests test the difference of coefficients between High-Tech (HT) and Low-Tech firms or between Medium-Large (ML) and Small firms. LR-test tests for no random effects in RE Logit. Goodness of fit is the Pearson chi-square test with 902 dof. P-values in brackets. Sensitivity = $P(\text{positive } outcome \mid Inno = 1)$; Specificity = $P(\text{negative } outcome \mid Inno = 0)$; Positive predictive value = $P(Inno = 1 \mid \text{positive } outcome)$. Correct classification takes all three probabilities into account to evaluate the model.

A Appendix 1: Sample Selection

The data used in this work are obtained by merging the two most recent waves (1995 and 1998) of a comprehensive survey on Italian manufacturing firms carried out by Mediocredito Centrale (MCC) every three years. Each wave reports standard balance sheet data for the previous three years (1992-94 and 1995-97 respectively) complemented by additional qualitative and quantitative information on several research issues including R&D and innovation. The 1995 and 1998 surveys include respectively 5415 and 4497 firms. As already mentioned in Section 2, all firms with more than 500 employees are included in each wave, whereas firms with less than 500 employees are selected with a stratified sampling method. Therefore, even after conditioning on survival, the probability of finding a small firm in two separate waves is small. To broaden our sample period we merged the two waves and obtained a reduced sample of 941 firms. This sample includes only those firms existing in both surveys. As it can be seen from Table A.1 and A.2, medium-large firms and firms operating in high-tech industries are over-represented compared to the original samples. This should not be surprising since it is an obvious implication of the sampling procedure described above.

Finally, we removed from the 941 firms those with missing values or inconsistencies for the variables used in the econometric estimates or with extreme values for the variables (both in level and long differences) reported in Table 1. The first and last percentiles have been used as lower and upper thresholds for the trimming procedure. After our cleaning and trimming procedures, we are left with 465 firms. As it can be seen from Table A.1, cleaning and trimming have led to a further over-representation of medium-large firms compared to the original samples.

Table A.1. Firms distribution by size in each sample, %

	1992-94 (5415)	1995-97 (4497)	Panel (941)	Panel (465)
Small	51.6	79.2	52.5	42.6
Medium-Large	48.4	20.8	47.5	57.4

Note: A firm with less than 100 employees is defined as "Small". It is "Medium-Large" otherwise.

Table A.2. Firms distribution by technology level, %

	1992-94 (5415)	1995-97 (4497)	Panel (941)	Panel (465)
High-Tech	33.2	33.0	40.6	40.4
Low-Tech	66.8	67.0	59.4	59.6

Note: A firm is defined as "High-Tech" if its main activity is one of the following: Chemicals, Machinery, Computers, Electrical Machinery, TV-Radio, Medical Apparels, Means of Transport. It is "Low-Tech" otherwise.

B Appendix 2: Variables Definition

Production (Y): computed as the sum of sales, capitalized costs and the change in work-in-progress and in finished goods inventories. All variables are deflated with the appropriate three digit production price index provided by the National Statistical Bureau (Istat).

Materials (M): computed as a Tornquist index of deflated materials and services. Materials equals purchases of materials net of the increase in raw materials inventories. Materials are deflated with an aggregate price index for raw materials and services are deflated with the GDP price index.

Fixed Investment (I): yearly investment in plants and machinery as reported in the questionnaire deflated with the aggregate business investment price index.

R&D Investment ($R\&D$) : yearly R&D investment as reported in the questionnaire deflated with a weighted average of the hourly earnings in manufacturing index (0.9) and the aggregate business investment price index (0.1). Firms are provided with a definition of what has to be considered as R&D investment consistent with the Frascati manual.

Fixed Capital (K): real fixed capital stock (at the end of the period), computed by a perpetual inventory method with a constant rate of depreciation ($\delta = 0.05$). The benchmark at the first year is the accounting value as reported in the balance sheet.

R&D Capital (G): real R&D capital stock (at the end of the period) computed by a perpetual inventory method with a constant rate of depreciation ($\delta = 0.15$). The benchmark for the first year is calculated assuming that the rate of growth in R&D investment at the firm level in the years before the first positive observation equals the average growth rate of industry level R&D between 1980 and 1991. The initial stock at historical costs is revalued using the average inflation rate for the R&D deflator during the same period.

Total Capital (TK): computed as the sum of fixed capital (K) and of R&D capital (G).

Non R&D Labor (L): number of employees at the end of the year. To avoid double counting, R&D workers are not included.

Innovation dummies: the process (product) innovation dummy takes the value 1 if the firm has declared to have introduced at least one process (product) innovation in the period covered by the survey (1992-94 or 1995-97), and zero otherwise. The generic innovation dummy takes the value 1 if the firm has declared to have introduced at least one product or one process innovation.

Age: age in 1992, computed as 1992 minus the year of birth as declared in the questionnaire.

Group Membership Dummy: equal to 1 if the firm is a member of a business group and zero otherwise.

Area Dummies: 4 geographical dummies have been included in all innovation equations (1 - North-West; 2 - North-East; 3 - Centre; 4 - South).

Each dummy takes the value 1 if a firm is located in that geographical area, zero otherwise.

Industry Dummies: 19 industry dummies have been included in all innovation equations reported in Tables 6 and 7 (15+16 - food, beverages and tobacco; 17 - textiles; 18 - clothing; 19 - leather; 20+36 - wood, wooden furniture and furniture; 21 - paper products; 22 - printing and publishing; 23 - oil refining; 24 - chemicals; 25 - rubber and plastics; 26 - non-metal minerals; 27 - metals; 28 - metal products; 29 - non-electric machinery; 30 - office equipment and computers; 31+32 - electric machinery, electronic material, measuring and communication tools, TV and radio; 33 - medical apparels and instruments; 34 - vehicles; 35 - other transportation). Each dummy takes the value 1 if the firm main activity is in that industry, and zero otherwise.