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R&D, Worker Training, and Innovation: Firm-level evidence*

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Abstract

This paper analyzes the effects of R&D and on-the-job training on innovation performance in a sample of Spanish manufacturing firms. The role of formal R&D activities has been intensively investigated, but little reserch has been carried out on the role of human capital, as measured by firm-sponsored worker training, and even less has addressed the interaction between both activities. We analyze the complementarity between the effects of R&D and training on firm innovation success while distinguishing between large and small firms. Our findings suggest that R&D is a key factor in explaining firm innovation performance and that worker training investment also has a significant effect albeit one of less magnitude. The results confirm a complementary relationship: on-the-job training reinforces the effect of R&D on innovation performance.

Key words: R&D, Worker Training, Innovation, Probit.

JEL Classification: L22, L11

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1. Introduction

Future countries growth must increasingly come from innovation-induced productivity growth. Innovation – the introduction of a new or significantly improved product, process or method – holds the key to boosting productivity. Research and development (R&D) is not the only factor that affects the rate of and capacity for innovation, in particular, the availability of a skilled technical workforce is important in establishing an environment that fosters innovation. Emphasizing the importance of education in innovation, Nelson and Phelps (1966) claim that "educated people make good innovators, so that education speeds the process of technological diffusion." Several papers have pointed out that R&D and human capital not only generate new information but also enhance the firm's ability to assimilate and exploit existing information. Worker skills are viewed as an important component of absorptive capacity and one that complements R&D.[1] Griffith *et al.* (2004) find evidence that both R&D and human capital are statistically and economically important in stimulating innovation as well as in productivity growth.[2]

There is a vast literature on the role of formal R&D activities in firm innovation performance. Less work has been done on analyzing the role of on-the-job training, and still less on its interaction and possible complementarities with R&D. Bartel and Lichtenberg (1987) show that highly educated workers have a comparative advantage as regards implementing and adjusting to new technologies. Teece (1986) suggests that profits from innovation depend on access to complementary capabilities, especially in marketing and distribution, without which the innovative idea cannot be profitably commercialized. Hashimoto (1991)

[1] See, for example, Cohen and Levinthal (1989).

[2] Using firm- and plant-level data, much empirical literature supports the hypothesis that R&D investment and technology adoption are important components of firm productivity (for surveys, see Griliches, 1998; Hall *et al.*, 2010). Several papers aim to quantify the contribution of training to firm productivity (see the survey of Blundell *et al.,* 1999). In particular, for US manufacturing firms, Black and Lynch (1996) find that the greater the proportion of time spent in formal off-the-job training, the higher the productivity. More recently, Dearden *et al.* (2006), find, based on a panel of British industries, that work-related training is associated with significantly higher productivity. Other empirical studies of interest are Bartel (1994, 1995, 2000), Baldwin *et al.* (1995), and Black and Lynch (1998).

shows that the efficient adoption of new technologies by Japanese firms can be at least partly attributed to their effective training strategies. More recently, Legros and Gallié (2011) find that training has a positive impact on the production of innovations in France. Rogers (2004) uses data on Australian firms to investigate the determinants of innovation, and he includes training among them.

Although both investments (R&D and training) seem to play a key role and may also possibly reinforce each other, it was not until recently that much attention was given to their interaction and complementarities. There is now an emerging literature that examines whether different types of knowledge investments reinforce one another.[3] Ballot *et al.* (2001, 2006) suggest that the interaction between R&D and training has a positive impact on French firm performance, and Bresnahan *et al.* (2002) demonstrate the existence of interactions among adoption of information technology, skills, and organizational design. Leiponen (2005) explores the interactions among firm employee skills, R&D collaboration activities, and innovation as well as their effects on profitability; she finds statistically significant complementarities between technical skills and innovation and between technical skills and R&D collaborative activities.

This paper aims (i) to analyze the relationship between R&D and worker training on firm innovation performance and (ii) to identify complementarities between both investments. We use a sample of Spanish manufacturing firms and present a simple theoretical framework to guide the empirical analysis, which assesses the effects of R&D and training on innovation performance. In analyzing this relationship, we focus on the differences between small and large firms. Research and development activities may be a particular challenge for small firms because of the associated high risk exposure, high fixed costs, high minimum investment required, and severe financial constraints. Smaller firms may therefore refrain from R&D and rely more on other practices in order to achieve innovation success.

[3] The study of complementarities between activities can be traced back to the theory of supermodularity (see Milgrom and Roberts, 1990, 1995). This theory has been applied in papers that look for complementarities among different bussiness strategies (e.g., Arora and Gambardella, 1990; Leiponen, 2005; Mohnen and Röller, 2005; Miravete and Pernias, 2006; Cassiman and Veugelers, 2006).

There is scarce evidence on the role of training in innovation that is based on Spanish data. Santamaria *et al.* (2009) use a panel data of Spanish manufacturing firms to explore how the innovation process depends on non formal R&D activities, such as training. These authors analyze the differences on this score between high-technology industries and industries with low (or medium-low) technology.

Analyzing the relationship between R&D and training –and their effects on innovation performance– is especially relevant for Spain, where the effort in both activities is below the European average. As Table 1 shows, Spain ranks at the bottom on the list of countries in both types of investments (see also Bassanini *et al.*, 2005). An explicit target of Spanish industrial policy is to increase firms' R&D levels. Toward this end, meaningful steps have been taken in public subsidies and tax credit. The design of public policies that reward one type of investment should consider the effects of such policies on firms' other complementary types of investment.

[Insert Table 1]

To conduct the empirical analysis, we use a panel of Spanish manufacturing firms over the period 2001—2006. There are several advantages to using this data set. It contains information on the R&D investments most commonly used in the literature as well as data about investment in on-the-job training, it also provides information on the performance of the innovation process. In particular, this data set contains time-varying information on the firms' product and process innovations, which enables a more precise analysis of different channels through which R&D and training are linked to innovation performance.

The results suggest a degree of complementarity between both activities. When their R&D is carried out in isolation, small and medium firms increase their probability of innovating by 25.5 percentage points; however, when R&D is added to training, the probability of innovating increases by 29 percentage points. Training also increases this probability (but to a lesser extent by only 4 percentage points) when it is carried out in isolation; when added to R&D, training increases the probability of innovating by 7.4 percentage points. These results differ according to the firm's size and the industry in which it operates.

The rest of the paper is organized as follows. Section 2 describes the data and the main facts about innovation, worker training, and R&D. Section 3 presents the theoretical framework, after which Section 4 describes the empirical strategy and reports the results. Section 5 concludes.

2. Patterns of innovation and investment in worker training and R&D

The data set used in this paper comes from the Encuesta Sobre Estrategias Empresariales (ESEE), a survey of Spanish manufacturing firms that is sponsored by the Ministry of Industry. In this survey, firms from 10 and 200 workers were chosen randomly (retaining 4% of them); all Spanish firms with *more* than 200 workers were asked to participate, and about 60% of them did so. The sample is fully representative of Spanish manufacturing firms in terms of firm sector (using NACE classification) and size.

Firms in the survey provide information regarding their characteristics and expenditures on R&D. Although the ESEE has been available since 1990, questions about training were not reported on an annual basis until 2001; hence we only use information from 2001 to 2006. Our sample contains a total of 9,584 observations, corresponding to 2,627 firms that have been observed for an average of four years during the period from 2001–2006. Approximately one third of these observations correspond to firms with more than 200 workers. All this information makes the ESEE especially well suited for conducting our analysis.

In what follows, we present some empirical regularities about firm participation in R&D and worker training (WT).

[Insert Table 2]

Table 2 summarizes the main characteristics of the database, distinguishing between large firms (with more than 200 workers) and small/medium-sized (SME) firms (with 200 or fewer workers). The table shows that investment in either R&D or WT activities is less frequent in SME firms than in large firms. For SME firms, 20% of the observations have positive R&D expenditures and 25% have positive WT expenditures. For large firms, these percentages are significantly higher: 72% and 76%, respectively.

Table 2 also provides information on two indicators of innovation output: *Innova*, which indicates the fraction of firms that have introduced at least one product or process innovation; and *Patent*, which shows the fraction of firms with at least one patent. On the one hand—and as expected, given their engagement in R&D and in WT activities—innovation is more frequent in large firms. Nevertheless, there are many large firms performing R&D that introduce neither product nor process innovations as well as some SME firms that do not perform R&D but do innovate. On the other hand, only 10% of the large firms obtain patents, and this is triple the percentage for SME firms. The empirical evidence thus indicates that (i) the characteristics of innovation differ depending on firm size and (ii) SME firms may rely on activities other than formal R&D to achieve innovation success (Rammer *et al.,* 2009).

[Insert Table 3]

Table 3 gives more details on firms' engagement in R&D and WT. The percentages and averages reported in the table are obtained by treating observations as a pool of data. We see that although 66% of the SME firms do not engage in either R&D or WT, only 10% of the large firms behave this way. The differences are less extreme with respect to participation in only one of these activities: for R&D, 9.7% of SME firms versus 13.5% of large firms; the respective values for WT are 13% versus 18%. A much greater difference is observed in the case of adopting both activities: 11% by SME firms versus 58% by large firms. The table also gives information on firms as classified into subsamples based on the technological level of the industries in which the firms operate. In high-technology sectors, fewer than 5% of the large firms are involved in neither R&D nor WT, whereas such total abstinence characterizes 45.5% of the SME firms. Clearly, simultaneous engagement in *both* activities is especially important to large firms in high-tech industries.

[Insert Table 4]

Table 4 provides information about firms' innovation performance while distinguishing among the proportion of firms introducing product innovation only, process innovation only or both types simultaneously. Several facts can be noted. First, process innovation is definitely more frequent than product innovation in all the subsamples. Second, innovation in large firms almost doubles the innovation in SME firms (in low-tech sectors, 51.7% of them exhibit some innovation compared with 25.9% of the SME firms). Third, the likelihood of innovation is greater in high-tech than in low-tech sectors. This difference is most pronounced for product innovation.

[Insert Table 5]

Table 5 reports on firms' innovation performance conditioned on their R&D and WT status. The table reveals that, for each particular combination of (R&D, WT) decisions, firm performance in terms of innovation is not much different between SME and large firms. Clearly, then, differences in innovation performance of the SME and large firms are due mainly to the differing proportion of firms in each of the (R&D, and WT) pair situations. The greater differences arise in the case of participation in both activities (rows 4 and 8), as product innovation seems to be more frequent in SME firms: 22% of them introduce this type of innovation exclusively, and an additional 30% did so jointly with process innovations. For large firms, the respective percentages are 13% and 35.5%.

Another relevant regularity is, on the one hand, the large proportion of innovating SME firms that participate in neither R&D nor WT. Fully 42% of the innovating SME firms can be so classified, given that 66% of all sample SME firms have no R&D or WT but 18% of these firms still do innovate. On the other hand, a relevant proportion of large firms did not successfully innovate despite being involved in both R&D and WT. These firms represent 42% of the non-innovating large firms, as 58% of them engage in both R&D and WT but 32% of the firms in this subset do not introduce any innovation.

3. Theoretical framework

Firms invest to increase knowledge so that they can develop and introduce innovations and thereby raise productivity and profitability. We focus on investment in R&D and worker training as the two main sources of innovation performance, which can take the form of product innovation (new or improved products) or process innovations. Although firms can use other informal channels to acquire knowledge and increase their ability to assimilate new information[4], there is wide consensus on the key roles played by R&D and WT in technological change and innovation performance.

Our goals are to measure the effect of both R&D and WT on innovation performance and to explore the extent of their complementarity. We assume that firm i will introduce an innovation, denoted I_{it}, if the increment to expected profits from doing so, π_{it}, is greater than the firm's cost of innovating (subscripts i and t index firms and time, respectively):

$$I_{it} = \begin{cases} 1 & \text{if} \quad \pi_{it}(x_t, z_{it}) - F_{it} > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where $\pi_{it}(x_t, z_{it})$ represents the increment to current gross profits associated with innovating in year t, assuming that the profit-maximizing level of innovation expenditures is always chosen. Here x_t is a vector of market-level variables that are exogenous to the firm (e.g., technological opportunities of the industry that the firm operates in), and z_{it} is a vector of firm-specific variables.

At this stage, no distinction is made between product and process innovation. We assume that both types have a positive effect on profits, though by different mechanisms. *Product* innovation typically affects demand, which increases consumers' willingness to pay for the new or improved product; *process* innovation enables firms production at a lower cost. Hence profit increases could result from an increase in revenues or a decrease in cost (or from both).

We use F_{it} to denote the direct monetary cost of innovating and assume that this cost depends on the firm's stock of R&D and worker training at the beginning of year. Because

[4] For example, new capital equipment (process innovation) or marketing for new and improved products

these stock variables are not observable, we proxy them via dummy variables that indicate which combination of the R&D and WT activities each firm chose in the previous year $t-1$:[5]

$$F_{it} = F_{it}^{0} - F_{i}^{1}(R_{it-1})(T_{it-1}) - F_{i}^{2}(R_{it-1})(1-T_{it-1}) - F_{i}^{3}(1-R_{it-1})(T_{it-1}); \qquad (2)$$

here R_{it-1} and T_{it-1} take the value 1 only if the firm made (respectively) R&D or WT investments in the previous period. Observe that if firm i undertook neither R&D nor WT in the last year then the cost of innovation is the highest, F_{it}^{0}. If firm i undertook both activities in the last period then innovation costs are reduced by the amount of F_{i}^{1} that is, $F_{it} = F_{it}^{0} - F_{i}^{1}$. If the firm invested in R&D but not in WT, then these costs would be $F_{it} = F_{it}^{0} - F_{i}^{2}$. Finally, for those firms that invested only in WT in the previous period, the cost is $F_{it} = F_{it}^{0} - F_{i}^{3}$. It is reasonable to assume that: $F_{i}^{1} > F_{i}^{2}$, F_{i}^{3}, which means that the minimum cost will be attained when the firm makes both investments. We may also reasonably assume that $F_{i}^{2} > F_{i}^{3}$; in other words, innovation cost is reduced more by R&D than by WT.

4. Empirical analysis

Our empirical model of a firm's innovation decision begins with the participation condition given by equation (1) and (2). The decision to innovate is then summarized by this discrete-choice equation:

$$I_{it} = \begin{cases} 1 & \text{if} \quad \left(\pi_{it} - F_{it}^{0}\right) + F_{i}^{1}\left(R_{it-1}\right)\left(T_{it-1}\right) + F_{i}^{2}(R_{it-1})(1-T_{it-1}) + F_{i}^{3}(1-R_{it-1})(T_{it-1}) \geq 0, \\ 0 & \quad \text{otherwise.} \end{cases}$$

We approximate $\pi_{it} - F_{it}^{0}$ as a reduced-form expression in exogenous firm and market characteristics that are observable in period t:[6]

$$\pi_{it} - F_{it}^{0} = \beta Z_{it-1} + \mu_{t} + \mu_{i} + \omega_{it}.$$

[5] This specification follows Roberts and Tybout (1997), who develop a model in which the decision to invest is subject to a sunk cost that must be paid prior to investment.

[6] Following, for example, Roberts and Tybout (1997) and Mañez *et al.* (2009).

The vector Z_{it-1} represents a set of firm and market characteristics. The variable μ_t is a time-specific component that takes into account business cycles and exogenous technical change that could affect the firm's innovation decision. The error term consists of two components: μ_i, the firm-specific effect capturing time-invariant unobserved firm heterogeneity (i.e. organizational or managerial ability, or simply non-observed environmental factors) that could influence either the level of profits that firms derive from innovations or the cost of those innovations; and ω_{it} is an unobserved shock. The latter term can be viewed as the random shocks (or uncertainty in the innovation processes) that are not observed by the econometrician but may affect the firm's decision to innovate in a given year.

4.1. Econometric model.—

Our goals are to identify factors that increase innovation performance and then measure their effects on the likelihood of innovating. We assume that the cost of introducing an innovation will be reduced to the same extent for all companies with the same (R&D, WT) pairing in the previous period. Thus we initially assume that $F_i^1 = \gamma_1$, $F_i^2 = \gamma_2$, and $F_i^3 = \gamma_3$. (this assumption will later be relaxed). The baseline econometric model for the innovation decision follows from the previous equations:

$$\begin{aligned} P(I_{it}=1) = \quad & \Phi(\gamma_1(R_{it-1})(T_{it-1})) + \gamma_2(R_{it-1})(1-T_{it-1}) + \gamma_3(1-R_{it-1})(T_{it-1}) \\ & +\beta Z_{it-1} + \mu_t + \underbrace{\mu_i + \omega_{it}}_{\varepsilon_{it}}) \end{aligned} \tag{3}$$

where $\varepsilon_{it} \sim N(0,1)$. As before, I_{it} is a binary indicator variable set equal to 1 if the firm introduces an innovation (and 0 otherwise). In building this variable we use two questions from the survey. The first is related to process innovation: each firm answer (Yes or No) whether any important modifications were made to its production process during year t. The second question asks whether the firm has obtained in year t any brand-new products or substantially modified products. Product novelties include performing new functions as well as incorporating new materials, components, design, and/or format. The dummy variable I_{it} takes the value 1 if the firm answers Yes to either of these two questions.

The explanatory variables include a constant and three dummy variables that take the value 1 or 0 in accordance with whether or not, in the previous year, the firm's innovation activities included R&D only, WT only, or both activities. We can test the null hypothesis (that investment in R&D and WT has a negligible effect on innovation output) by testing for whether the γ_j are jointly equal to zero. This specification also allows us to test for complementarity between both activities by comparing the magnitude of their respective coefficients, as we will see in the next section.

The rest of the explanatory variables included in the vector Z_{it-1} control for a set of firm characteristics that are likely to determine the innovation output. The size of the firms is measured in terms of the *total number of employees* (in logs). *Number of competitors* is a dummy variable that takes the value 1 when the firm states that there are at least two but fewer than ten other firms with a significant market share in its main market. The (log of) *price-cost margin* is approximated as the difference between the value of gross output and the variable costs of production, divided by the value of gross output.[7] *Age* measures firm experience in terms of the number of years since the firm's founding year; this variable captures the potential learning-by-doing effects of experience. We also include a dummy variable indicating whether or not the firm manufactures more than one product, *Multiproduct firm,* and another that takes the value 1 if the firm exports, *Exporter firm.*

The homogeneity of the product is taken into account by including a dummy variable that takes the value 1 when the firm states that its products are highly *standardized* (i.e. mostly the same for all buyers). *Expansive market* takes the value 1 when the firm reports that demand is increasing, and likewise for *Recessive market* when demand is contracting. *Geographical location* measures the regional spillover and takes the value 1 only for firms located in regions with a higher level of R&D and skilled workers (i.e. Madrid, Catalonia and Basque country).

We include two dummy variables indicating the complexity of the production technologies: *Rob/Cad/Cam* takes the value 1 if the firm uses robotics or computer-aided design or computer-aided manufacturing; *SSF* takes the value 1 if the firm uses numerical control

[7] The gross output value is computed as sales plus stocks variation plus other revenues. The variable costs of production are measured as intermediate consumption (raw materials and services) plus labor costs.

machines of flexible systems to manufacturing.

High technological opportunities is a dummy variable indicating whether the firm operates in high or medium-high sectors: Chemical products; Agricultural and industrial machinery; Office and data processing machinery; Electrical goods; Motor vehicles; Other transport equipment. This variable measures differences across industries in terms of technological capabilities or opportunities, which are considered to influence both the cost of innovation and its profitability.

We lag all firm characteristics and other exogenous variables by one year, in order to avoid potential simultaneity problems. Finally, the μ_t denote year fixed effects that control for exogenous technological change as well as any macroeconomic shock. The error term, ε_{it}, has two components: μ_i is a firm-specific effect; and ω_{it} is an unobserved shock.

The main econometric issue refers to unobserved firm heterogeneity. First, we estimate a baseline probit model without unobserved heterogeneity and with robust standard errors clustered at the firm level to control that observations of the same firms are related over time.

Second, we assume that the error term is, $\varepsilon_{it} = \mu_i + \omega_{it}$, where $\omega \sim N(0,1)$ and $\mu \sim N(0, \sigma_u)$, and μ_i is uncorrelated with the independent variables. One advantage of the random effects probit estimation is that it explicitly controls for firm-unobserved heterogeneity but it does not take into account the correlation of the firm-specific effect with the regressors. Finally, we use Chamberlain's (1984) random effects probit model; this model allows dependence between μ_i and the firm's characteristics included in the vector Z, but the dependence must be restricted in some way. Specifically, we assume that this unobserved individual heterogeneity depends on the time-averaged continuous variables included in vector Z: $\mu_i = \lambda_0 + \lambda \overline{Z}_{1i} + c_i$, where $\overline{Z}_{1i}$ is the firm average of Z_{1it}. We assume further $c_i \sim N(0, \sigma_c)$ and $c_i \perp \overline{Z}_{1i}$ (cf. Wooldridge, 2001).

5. Results

This section describes the results of the estimation as well as the effects of R&D and WT on the probability of innovating. Table 6A presents the coefficients obtained by estimating equation (3), under the three different probit models, for the SME firms.[8] The first and second columns correspond to the probit model with robust standard errors clustered at the firm level; the third and fourth columns present (respectively) the random effects model and the Chamberlain random effects probit model.

[Insert Table 6]

The variables of interest are the lagged dummies of investment in R&D and training. The estimated coefficients for the three variables included are significant, which suggests a positive effect of investing in both activities (either simultaneously or separately). The coefficients increase when we consider the fixed firm-specific effects (columns 3 and 4) in comparison with the probit model that includes the control variables (column 2), although the correction incorporated in the last column changes the coefficients only slightly when compared with column 3.

As it is well known, the estimated coefficients of a probit model cannot be directly interpreted as a marginal effect, although we can compare the magnitudes and the sign. The corresponding point estimates suggest that firms with past experience in R&D and/or WT are more likely to innovate in the current period, although the magnitudes of the marginal effects are substantially different for the two activities (see section 5.1 for details). As expected, experience in R&D has a much greater effect on the likelihood of innovation than does training.

With regard to the other firm-level determinants of innovation performance, the results are consistent with those found in previous literature. The positive and significant coefficient of our exporter dummy variable suggests that exporter firms are more likely to innovate than are other firms. The multiproduct firm variable also has a positive and significant impact.

[8] Table 6' provide the estimated coefficients for the subsample of large firms.

These results indicate that exporter and multiproduct firms find it more profitable than do other firms to introduce a new product or process and that higher competitive pressure stimulates innovation. Note also that size, as measured by the log of total employment, has a positive impact on the probability of innovating under the random effects probit models (columns 3 and 4).

The impact of number of competitors becomes insignificant in the random effects probit models, and this is true also of the impact of price-cost margin (once we include the mean of this variable as a control). The extend of product standardization, a proxy for product homogeneity, has no impact on the probability of innovating. This negligible effect can be explained if it affects in opposite ways on product and process innovations; according to Huergo and Moreno (2011), the effect product homogeneity might be positive for product innovations and negative for process innovations.

Our dummy variables capturing the dynamism of the market in which the firm operates have the expected sign. An expansive market increases the incentives to innovate because in that case as firms expect higher future profits. In contrast, a recessive market reduces the future profits of innovation, although this effect is not significant. Finally, firms in high-tech sectors and firms that incorporate sophisticated production technologies are more likely to introduce innovations.

5.1. Analysis of complementarity.—

We follow Cassiman and Veugelers (2006) in stating that *complementarity* exists between two firm strategies only if "adding an activity while the other activity is already being performed has a higher incremental effect on performance than adding the activity in isolation." In our context this means that, in the presence of complementarities, the increase in innovation probability that is due to investment in training WT will be higher the when training is added to R&D than when training occurs in isolation. That is,

$$P(I=1|R=1,T=1)-P(I=1|R=1,T=0) \geq P(I=1|R=0,T=1)-P(I=1|R=0,T=0).$$

In order to estimate directly the impacts of WT and R&D on the likelihood of innovating, we first calculate the the fitted probabilities and then calculate the average marginal effect of each investment.

We summarize the fitted probabilities computed using the parameters reported in the fourth column of Table 6 for SME firms (and 6' for large firms). Hence the probability of innovating when firms have experience in both activities is calculated as $P(I_{it} = 1|R_{it-1} = 1, T_{it-1} = 1, \widehat{\beta}Z_i) = P(I_{it} = 1|1, 1) = \Phi(\widehat{\alpha} + \widehat{\gamma}_1 + \widehat{\beta}Z_{it})$. Likewise, the probability of having experience only in R&D is $P(I_{it} = 1|1, 0) = \Phi(\widehat{\alpha} + \widehat{\gamma}_2 + \widehat{\beta}Z_{it})$, of having experience only in WT is $P(I_{it} = 1|0, 1) = \Phi(\widehat{\alpha} + \widehat{\gamma}_3 + \widehat{\beta}Z_{it})$, and of having experience in neither activity is $P(I_{it} = 1|0, 0) = \Phi(\widehat{\alpha} + \widehat{\beta}Z_{it})$.

Table 7 reports the average fitted probabilities for each combination of investment while distinguishing between small and large firms as well as between high- and low-tech industries. The first column of the table shows that the average fitted probability of innovating for SME firms ranges from 10% (for firms with no experience in either innovation activity) to 43% (for firms with experience in both activities); the respective probabilities range from 26% to 68% for large firms). We also find that all probabilities are higher for firms in high-tech industries than for those in lower for low-tech industries.

[Insert Table 7]

We use the predicted probabilities to obtain the average marginal effect of each activity when it is undertaked in isolation as well as the effect of adding one activity to the other. With a linear model, the estimated parameters directly yield the effects of interest; however, since the estimated model is nonlinear, we must calculate the effect of each investment on the probability of innovating.

On the one hand, we calculate the effect of adding R&D when the firm already undertakes WT as

$$AME1 = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it} = 1|1, 1) - P(I_{it} = 1|0, 1)] = \frac{1}{N}\sum_{i=1}^{N}[\Phi(\widehat{\alpha}+\widehat{\gamma}_1+\widehat{\beta}Z_{it})-\Phi(\widehat{\alpha}+\widehat{\gamma}_3+\widehat{\beta}Z_{it}].$$

and the effect on the probability of innovating due to experience only in R&D as:

$$AME2 = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1|1,0)-P(I_{it}=1|0,0)] = \frac{1}{N}\sum_{i=1}^{N}\left[\Phi(\widehat{\alpha}+\widehat{\gamma}_2+\widehat{\beta}Z_{it})-\Phi(\widehat{\alpha}+\widehat{\beta}Z_{it})\right].$$

If $AME1 \geq AME2$ we can suggest that complementarity applies.

Similarly it is obtained the effect of adding WT when the firm is already undertaking R&D and the effect on the probability of innovating due to experience only in WT only, respectively, $\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1|1,1)-P(I_{it}=1|1,0)]$ and $\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1|0,1)-P(I_{it}=1|0,0)]$

Table 8 presents the results again distinguishing by firm size and by industry technology level. The values reported in column 1 suggest a degree of complementarity between both activities for SME firms. The second row indicates that, when R&D is added to training, firms increase their probability of innovating by 29 percentage points; there is less of an increase (25 percentage points) when R&D is carried out in isolation (third row). On average, R&D experience is more effective when firms have also experience in WT (that is, $AME1 \geq AME2$).

[Insert Table 8]

Although worker training also increases firms' innovation, it does so to a lesser extent. When WT is carried out in isolation, the firm's probability increases by 4 percentage points (last row); if WT is combined with existing R&D, that probability increases by 7 percentage points.

The results in columns 2 and 3 show differences by industries. First, the magnitude of all the average marginal effects estimated is greater for the high-tech industries. Second, complementarity is present in both types of industries, though its magnitude is greater for low-tech industries.

These general patterns are similar for the group of large firms. We should highlight two differences in particular. Comparing the figures in column 4 with those in column 1 we can see that both training and R&D are more effective for large firms than for the smaller ones –not only when they are carried out in isolation but also when they are added to existing

R&D or WT. Moreover, the heterogeneity in the magnitude of these effects is substantially lower in the group of large firms.

6. Conclusions

This paper explores the effects of firm R&D and worker training experience on innovation performance. Earlier studies have dealt with the effect of R&D or human capital on firm performance without taking into account the possible complementarity between these investments. Our study focuses explicitly on the interactions between WT and R&D activities at the firm level and measures their mutual complementarity.

In summary, the empirical evidence presented here confirms that R&D is a key factor in explaining firm innovation performance. Worker training investment also has a significant effect, but one of lower magnitude. Finally, R&D (training) is more effective for large than for the small firms, both when it is carried out in isolation and also when it is added to training (R&D).

The results reported in this paper establish a complementary relationship: worker training reinforces the effect of R&D on innovation performance. Complementarities are present in both small and large firms, although the magnitude is less for the latter. However, complementarity seems to be independent of the technological level of the sector in which the firm operates.

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Table 1. Training and R&D implication by countries (%)

	WT[1]	R&D[2]
Finland	0.34	2.39
Denmark	0.42	1.59
France	0.15	1.44
Belgium	0.14	1.29
Austria	0.16	1.24
Netherlands	0.07	1.17
Britain	0.41	1.07
Spain	0.10	0.94
Ireland	0.09	0.86
Italy	0.06	0.77

[1]Percentage of the employed population between 35-54 years who engage in training

[2]Percentage of employed people working in R&D (in full-time equivalent)

Table 2. Participation in R&D and WT activities and firm innovation performance (%)

	Small and Medium Firms					Large Firms				
Year	N[1]	R&D	WT	Innova	Patent	N[1]	R&D	WT	Innova	Patent
2001	1092	19.9	24.1	33.2	2.7	491	70.9	73.3	59.3	9.2
2002	1125	20.2	24.9	29.9	3.8	468	73.1	78.4	59.0	11.1
2003	907	19.5	21.2	24.7	2.7	418	70.1	73.0	49.5	8.9
2004	893	19.8	20.8	26.5	2.8	425	73.2	74.4	53.4	10.6
2005	1258	22.6	25.3	29.7	4.7	547	71.3	75.9	55.4	10.6
2006	1431	21.7	26.5	30.1	3.3	529	71.3	81.3	55.6	11.3
Total	6706	20.8	24.1	29.3	3.4	2878	71.6	76.2	55.5	10.3

[1]Number of firms

Table 3. Innovation input choices by size and type of industry (%)

	Small and Medium Firms			Large Firms		
	All	High Tech. Industries	Low Tech. Industries	All	High Tech. Industries	Low Tech. Industries
No R&D or WT	66.2	45.7	72.1	10.3	4.6	13.8
Only R&D	9.7	14.5	8.3	13.5	12.4	14.2
Only WT	13.1	14.7	13.6	18.1	11.1	22.3
Both investments	11.1	25.1	7.1	58.1	71.9	49.7
Observations	6706	1500	5206	2878	1090	1788

Table 4. Innovation performance by size and type of industry (%)

	Small and Medium Firms			Large Firms		
	All	High Tech. Industries	Low Tech. Industries	All	High Tech. Industries	Low Tech. Industries
No innovation	70.7	58.9	74.1	44.5	38.3	48.3
Only product	7.7	13.7	6.0	11.0	12.9	9.8
Only process	14.0	14.7	13.8	19.0	18.6	19.0
Both innovations	7.6	12.8	6.1	25.7	30.2	22.9
Observations	6706	1500	5206	2887	1090	1788

Table 5. Innovation input choices and innovation performance (%)

	No Innovation	Only Product	Only Process	Both Innovations
SME Firms				
No R&D or WT	81.6	4.0	11.7	2.6
Only R&D	43.4	19.2	17.4	20.0
Only WT	70.3	5.3	19.6	4.8
Both investments	30.0	22.3	17.8	29.9
All	70.7	7.7	14.0	7.6
Large Firms				
No R&D or WT	80.1	3.0	13.8	3.0
Only R&D	41.0	17.0	22.2	19.9
Only WT	65.6	4.2	18.9	11.4
Both investments	32.4	13.1	19.0	35.5
All	44.5	11.0	18.9	25.7

Table 6. Innovation Performance. Small and medium firms

	(1) Coeficient (Stand. Err.)	(2) Coeficient (Stand. Err.)	(3) Coeficient (Stand. Err.)	(4) Coeficient (Stand. Err.)
Intercept	-0.922*** (0.039)	-1.259*** (0.139)	-2.129*** (0.232)	-2.577*** (0.336)
Only R&D $_{t-1}$	0.966*** (0.093)	0.802*** (0.097)	1.010*** (0.122)	0.988*** (0 123)
Only Training $_{t-1}$	0.326*** (0.083)	0.151* (0.086)	0.219** (0.110)	0.211* (0.110)
Both $_{t-1}$	1.283*** (0.085)	1.001*** (0.096)	1.206*** (0.131)	1.200*** (0.131)
Log total employment$_{t-1}$		0.036 (0.040)	0.116* (0.063)	0.190* (0.114)
Number of competitors$_{t-1}$		0.128** (0.060)	0.120 (0.080)	0.109 (0.080)
Log of price cost margin$_{t-1}$		0.005*** (0.002)	0.005* (0.003)	0.000 (0.003)
Age$_{t-1}$		-0.002 (0.002)	-0.002 (0.004)	-0.001 (0.008)
Multiproduct firm Dummy$_{t-1}$		0.134 (0.092)	0.246** (0.124)	0.253** (0.124)
Exporter firm Dummy$_{t-1}$		0.301*** (0.067)	0.386*** (0.094)	0.380*** (0.094)
Standarized product Dummy$_{t-1}$		-0.057 (0.064)	-0.041 (0.091)	-0.041 (0.091)
Expansive market Dummy$_{t-1}$		0.249*** (0.062)	0.242*** (0.082)	0.240*** (0.082)
Recessive market Dummy $_{t-1}$		-0.007 (0.070)	-0.127 (0.091)	-0.122 (0.092)
Geographical localization Dummy		0.042 (0.064)	0.144 (0.101)	0.139 (0.102)
Rob/Cad/Cam Dummy$_{t-1}$		0.029 (0.064)	0.101 (0.090)	0.089 (0.090)
SSF Dummy$_{t-1}$		0.141** (0.078)	0.281*** (0.107)	0.286*** (0.107)
High technological opportunities		0.085 (0.081)	0.251** (0.119)	0.271** (0.119)
Year dummies		included	included	included
Number of observations	4799	4799	4799	4799
Log-likelihood	-2523.6	-2449.8	-2093.4	-2089.4
% corrected pred 1's	56.9	59.1	47.4	46.6
% corrected pred 0's	75.6	75.4	86.6	86.2
Pseudo R-squared	0.11	0.13		
σ			1.345 (0.072)	1.344 (0.072)
ρ			0.644 (0.025)	0.644 (0.025)

Table 6'. Innovation Performance. Large Firms

	(1)	(2)	(3)	(4)
	Coeficient (Stand. Err.)	Coeficient (Stand. Err.)	Coeficient (Stand. Err.)	Coeficient (Stand. Err.)
Intercept	-0.770*** (0.118)	-1.548*** (0.431)	-1.923*** (0.681)	-0.731 (0.971)
Only R&D $_{t-1}$	0.959*** (0.151)	0.898*** (0.151)	0.874*** (0.217)	0.894*** (0.217)
Only Training $_{t-1}$	0.265* (0.144)	0.197 (0.146)	0.225 (0.204)	0.241 (0.205)
Both $_{t-1}$	1.138*** (0.131)	1.013*** (0.137)	1.169*** (0.199)	1.197*** (0.200)
Log total employment$_{t-1}$		0.128** (0.065)	0.178* (0.106)	-0.052 (0.167)
Number of competitors$_{t-1}$		0.049 (0.091)	0.130 (0.124)	0.131 (0.124)
Log of price cost margin$_{t-1}$		0.005 (0.003)	0.007 (0.005)	0.005 (0.006)
Age$_{t-1}$		0.001 (0.003)	-0.002 (0.004)	–0.002 (0.006)
Multiproduct firm Dummy$_{t-1}$		0.032 (0.130)	0.110 (0.177)	0.113 (0.177)
Exporter firm Dummy$_{t-1}$		-0.067 (0.163)	-0.071 (0.249)	-0.038 (0.250)
Standarized product Dummy$_{t-1}$		-0.081 (0.092)	0.020 (0.144)	0.009 (0.145)
Expansive market Dummy$_{t-1}$		0.120 (0.080)	0.029 (0.109)	0.024 (0.110)
Recessive market Dummy $_{t-1}$		0.030 (0.101)	-0.250* (0.140)	-0.253* (0.141)
Geographical localization Dummy		0.054 (0.088)	0.062 (0.147)	0.083 (0.148)
Rob/Cad/Cam Dummy$_{t-1}$		0.299*** (0.097)	0.461*** (0.141)	0.449*** (0.141)
SSF Dummy$_{t-1}$		0.071 (0.088)	0.233* (0.124)	0.229* (0.124)
High technological opportunities		-0.059 (0.094)	0.080 (0.158)	0.064 (0.159)
Year dummies		included	included	included
Number of observations	2086	2086	2086	2086
Log-likelihood	-1325.3	-1292.5	-1089.7	-1087.9
% corrected pred 1's	88.7	73.1	73.1	73.3
% corrected pred 0's	44.9	60.0	57.5	58.6
Pseudo R-squared	0.08	0.10		
σ			1.453 (0.108)	1.454 (0.108)
ρ			0.679 (0.032)	0.679 (0.032)

Table 7. Predicted probability of innovation success

	Small and medium firms			Large firms		
	All firms	High Tech.	Low Tech.	All firms	High Tech.	Low Tech.
$P(I_{it} = 1\|1, 1)$	0.435	0.574	0.394	0.682	0.734	0.669
$P(I_{it} = 1\|1, 0)$	0.361	0.496	0.322	0.577	0.638	0.567
$P(I_{it} = 1\|0, 1)$	0.145	0.234	0.119	0.342	0.408	0.339
$P(I_{it} = 1\|0, 0)$	0.106	0.178	0.85	0.265	0.301	0.241
$P(I_{it} = 1)$	0.187	0.343	0.141	0.560	0.649	0.507

Table 8. Average marginal effect (AME) of R&D and WT

	Small and medium firms			Large firms		
	All firms	High Tech.	Low Tech.	All firms	High Tech.	Low Tech.
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,1)-P(I_{it}=1\|0,0)]$	0.328	0.395	0.309	0.417	0.416	0.417
	(0.09)	(0.06)	(0.09)	(0.05)	(0.06)	(0.04)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,1)-P(I_{it}=1\|0,1)]$	0.290	0.340	0.275	0.340	0.336	0.342
	(0.07)	(0.05)	(0.07)	(0.04)	(0.05)	(0.03)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,0)-P(I_{it}=1\|0,0)]$	0.255	0.318	0.237	0.312	0.316	0.309
	(0.08)	(0.06)	(0.08)	(0.04)	(0.05)	(0.04)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,1)-P(I_{it}=1\|1,0)]$	0.074	0.077	0.073	0.105	0.100	0.108
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|0,1)-P(I_{it}=1\|0,0]$	0.039	0.055	0.034	0.077	0.081	0.075
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Note: Standard deviation of the AME in parenthesis