R&D, Worker Training, and Innovation: Firm-level evidence[‡]

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Abstract

Firms that invest in R&D and at the same time in worker skills (on-the-job training) are expected to be more successful in innovation, but the extent to which one investment reinforces the effect of the other on innovation performance is less evident. This paper analyzes the effects of R&D and of worker training on innovation using a sample of Spanish manufacturing firms in order to identify complementarities between both investments. Our findings confirm that R&D is a key factor in explaining firm innovation. It also shows that worker training investment has a significant effect, albeit one of less magnitude. The results confirm a complementary relationship: training reinforces the effect of R&D on innovation performance. However, the effects vary depending on firm size and industry. In addition, we find that the complementarity is larger in those firms that are less likely to be innovators.

Key words: R&D, Worker Training, Innovation, Probit models, Marginal Effects.
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1. Introduction

Innovation -the introduction of a new or significantly improved product, process or method- holds the key to boosting firm productivity and economic growth.[1] Innovation can be influenced by a wide range of factors. Obviously, research and development (R&D) plays a crucial role in the rate of and capacity for innovation but, it is not the sole mechanism used to obtain innovations. As innovation requires a variety of workers' skills, human capital is essential. Formal education is basic in human capital and the national education systems should provide it. Yet, training (and, particularly, on-the job training) also plays a key role in providing the wide range of skills needed to enhance the overall capacity to innovate (OECD, 2010). Nelson and Phelps (1966), emphasizing the importance of education in innovation, claim that “educated people make good innovators, so that education speeds the process of technological diffusion”. In this line, Bartel and Lichtenberg (1987) show that highly educated workers have a comparative advantage in regard to implementing and adjusting to new technologies.

R&D and human capital not only generate new knowledge but also are important components of firms' absorptive capacity which is crucial in stimulating innovation and, after all, productivity growth.[2] This paper aims to analyze the relationship between R&D and worker training in firm innovation performance in order 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

[1]For a detailed definition of innovation, see the Oslo Manual (OECD, 2005).

[2] Cohen and Levinthal (1989) analyze the role of R&D not only in the generation of new information, but also in enhancing the firm's ability to assimilate and exploit existing information. More recently, Griffith et al. (2004) find empirical evidence that the effects of both R&D and human capital on productivity are quantitatively important.

R&D and training on the likelihood of innovating. In analyzing this relationship, we explore the differences between small and large firms. Research and development activities are particularly challenging 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 -among them, worker training- in order to achieve innovation success. Thus, we conduct the empirical analysis for SMEs and large firms separately.

There is extensive literature on the role of formal R&D activities in firm performance and a significant number of papers analyze the role of on-the-job training. Using firm- and plant-level data, the empirical literature supports the hypothesis that R&D investment and innovation are important components of firm productivity (see the surveys of Griliches, 1998, Hall *et al.*, 2010, and Hall, 2011). Other papers aim to quantify the contribution of training to firm productivity and they usually find a positive impact (see the surveys of Blundell *et al.,* 1999, and Bartel, 2000). In particular, Conti (2005) and Dearden *et al.* (2006) find that R&D and training are associated with higher productivity for Italian and British firms, respectively, and Boothby *et al.* (2010) find that firms that adopt advanced technologies and at the same time provide strategic training are, on average, more productive. [3]

A number of studies are devoted to analyzing the relevance of R&D and training on innovation. Becheikh *et al.* (2006) provides a revision of empirical studies on the determinants of innovation in the manufacturing sector. Laursen and Foss (2003) found that human resources management practices -in particular, internal training and the combination of internal and external training- influence innovation performance positively. Rogers

[3] Other empirical studies of interest are Bartel (1994, 1995), and Black and Lynch (1996).

(2004) uses data on Australian firms to investigate the determinants of innovation; he includes training among them, but does not find a significant effect. More recently, Zhou *et al*. (2011) found evidence that training and R&D have a positive impact on the firm innovation performance in the Netherlands, as these investments contribute positively to new product sales. Using data for French firms, Gallié and Legros (2012) also find that training and R&D have a positive impact on the production of innovations.

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. An emerging literature now examines whether different types of knowledge investments reinforce one another.[4] For example, Ballot *et al.* (2001) analyze the effects of human and technological capital on productivity in a sample of large French and Swedish firms. They obtain some positive interactions between R&D and training, though the results vary by country.[5] Leiponen (2005) explores the complementarities among firm employee skills, R&D collaboration activities, and innovation, by analyzing their effects on profitability; she finds statistically significant complementarities between technical skills and innovation, as well as between technical skills and R&D collaborative activities.

There is scarce evidence on the role of training in innovation based on Spanish data. Santamaría *et al.* (2009) use a panel data of Spanish manufacturing firms to explore how the innovation process depends on non-formal R&D activities. They find that activities

[4] 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 business strategies (e.g., Arora and Gambardella, 1990; Bresnahan et al., 2002; Mohnen and Röller, 2005; Miravete and Pernias, 2006; Cassiman and Veugelers, 2006).

[5] Ballot et al. (2006) use the same data sources to explore the effects of investment in physical capital, training and R&D on productivity and wages. They assess how the benefits of these investments are shared between the firm and the workers.

such as design, the use of advanced machinery and training are important in understanding the innovation process. This is especially so in low-tech industries. Nevertheless, they do not consider the possible interactions or complementarities between R&D and non-formal R&D activities.[6]

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 of 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. To this end, meaningful steps have been taken in public subsidies and tax credits. Moreover, there are public policies that promote worker training. These policies are an important part of the active labor market policies in Spain. The design of public policies that reward one type of investment should consider the effects of such policies on other complementary investments. Thus, it is relevant for policy makers to identify the existence of complementarities. According to the Oslo Manual (OECD, 2005): "A broad understanding of the distribution of innovation activities across industries is of obvious importance for innovation policy. An important goal is to understand the role of R&D and non-R&D inputs in the innovation process and how R&D may be interrelated with other innovation inputs". Our paper seeks to provide evidence on this issue.

[Insert Table 1]

To conduct the empirical analysis, we use an unbalanced panel of Spanish manufacturing firms over the period 2001-2006. There are several advantages to using this

[6] Santamaría et al. (2009) use a balanced sample of firms from 1998 to 2002 that come out of the same data source as ours. Yet, their training variable is different because they use information arising from a question that only appears in the questionnaire every four years.

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 annual information on the firms' product and process innovations. To identify the complementarity effects, we first specify and estimate a probit model, and then we calculate specific marginal effects for the relevant variables.

The results suggest a degree of complementarity between both activities. In small and medium firms, R&D increases the probability of innovating by 19.8 percentage points on average when it is carried out in isolation; while, when R&D is added to training, it is more effective, given that it increases the probability of innovating by 20.9 percentage points. Training also increases the probability but, to a lesser extent: by only 3.7 percentage points when it is carried out in isolation; by 4.8 percentage points, when it is added to R&D. Thus, on the one hand, training definitively has a much lower effect on innovating than R&D, but it clearly reinforces the effect of R&D on the likelihood of a firm becoming a successful innovator. On the other hand, we find that the magnitude of the complementarities varies with the probability of innovating, and it almost disappears when this probability is very high. These results indicate that complementarities are more present when firms have more difficulties to innovate. Similar conclusions are obtained for large firms.

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. Section 4 describes the empirical strategy and Section 5 reports the results. Section 6 concludes. The appendix provides the variable definitions and the descriptive statistics.

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 employing from 10 to 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 on a wide number of firm characteristics, including expenditures on R&D (internal and external) and external expenditures on different types of worker training (in software and information technology training, in language training, in engineering and technical training, training in sales and marketing, and training in other subjects). Although the ESEE has been available since 1990, questions about training were not reported on an annual basis until 2001; hence we use information from 2001 onwards.

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.[7] 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]

[7] 37% of the firms are observed every year throughout the period studied.

Table 2 summarizes the main characteristics of the database, distinguishing between large firms (with more than 200 workers) and small/medium-sized firms (with 200 or fewer workers, SMEs hereafter). The table reveals that investment in either R&D or WT activities is less frequent in SMEs than in large firms. For SMEs, 20.8% of the observations have positive R&D expenditures and 24.1% have positive WT expenditures. For large firms, these percentages are significantly higher: 71.6% and 76.2%, 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 SMEs 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 SMEs. The empirical evidence thus indicates that (i) the characteristics of innovation differ depending on firm size and (ii) SMEs 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.[8] We see that although 66% of the SMEs 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 SMEs versus 13.5% of large firms; the respective

[8] The percentages and averages reported in all tables are obtained by treating observations as a pool of data.

values for WT are 13% versus 18%. A much greater difference is observed in the case of adopting both activities: 11% by SMEs 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 absence of R&D and WT characterizes 45.7% of the SMEs. 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 SMEs (in low-tech sectors, 51.7% of large firms exhibit some innovation compared with 25.9% of the SMEs). 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 explores firms' innovation performance depending 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 SMEs and large firms. Clearly, then, differences in innovation performance of the SMEs and large firms are due mainly to the differing proportion of firms in each of the (R&D, WT) pair situations. In the case of participation in both activities (rows 4 and 9), an interesting regularity arises. Product innovation seems to be more frequent in SMEs: 22.3% of them introduce this type of innovation exclusively, and an additional 29.9% did so jointly with process innovations. For large firms, the respective percentages are 13.1% and 35.5%.

Another two relevant facts are the following. On the one hand, the large proportion of innovating SMEs that participate in neither R&D nor WT. Fully 41.6% of the innovating SMEs can be so classified, given that 66.2% of the SMEs have no R&D or WT but 18.4% 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 42.3% of the non-innovating large firms, as 58.1% of them engage in both R&D and WT but 32.4% 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,[9] 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 effects of both R&D and WT on innovation performance and to explore the existence of complementarity between these two investments. We

[9] For example, acquisition of new capital equipment or marketing for new and improved products.

assume that firm *i* will introduce an innovation, denoted I_{it}, if the increment to expected gross profit from doing so, π_{it}, is greater than the cost of introducing an innovation, F_{it} (subscripts *i* and *t* index firms and time, respectively):

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

where $\pi_{it}(x_t, z_{it})$ is the difference, in year *t*, between the expected gross profit when innovating and the expected gross profits when the firm do not innovate, assuming that the profit-maximizing level of innovation expenditures is 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.[10]

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. Profit increases could result from an increase in revenue or a decrease in cost (or from both). *Product* innovation typically increases consumers' willingness to pay for the new or improved product, which affects demand; *process* innovation enables production at a lower cost.

We use F_{it} to denote the direct monetary cost of innovating and assume that this cost depends on the firm's stocks of R&D and worker training at the beginning of year. Previous experience in R&D and WT increases the stock of knowledge in the firms and thereby contribute to strengthening the skills required to introduce innovations. This can help to

[10] Our framework has similarities with the model developed by Roberts and Tybout (1997) to analyze export-market participation in the presence of sunk costs, as well as with the model used by Mañez et al. (2009) to analyze the existence of sunk R&D costs associated to performing R&D. They find that prior experience in R&D influences the current decision to invest in R&D by reducing the sunk cost associated to R&D activities.

reduce the current cost of innovating.[11] In this line, the OECD (2010) report stands out that "Innovation requires a wide variety of skills, as well as the capacity to learn, adapt or retrain, particularly following the introduction of radically new products and processes. Empowering people to innovate relies not only on broad and relevant education, but also on the development of wide-ranging skills that complement formal education".

Then, we proxy F_{it} via dummy variables that indicate which combination of the R&D and WT activities each firm chose in the previous year *t-1:*

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

where 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 cost is 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 this cost 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.

Equations (1) and (2) imply that the probability of innovating will be greater when the firm has incurred in R&D and/or WT in the previous period. In order to identify the

[11] The Oslo Manual (OECD, 2005) claims that "Much innovation knowledge is embodied in people and their skills, and appropriate skills are needed to make intelligent use of external sources or codified knowledge".

existence of complementarity between R&D and WT, we consider the usual definition of complementarity: firm's activities are complements if doing any one of them increases the returns to doing the other (Milgrom and Roberts, 1990, 1995). In our case, we conclude that complementarity exists if the increase in the probability of innovating when R&D (WT) is added to WT (R&D) is *greater* than the increase in the probability of innovating when R&D (WT) is carried out in isolation.

4. Empirical analysis

Our empirical model is based on the participation condition given by equations (1) and (2). The decision to innovate is then summarized by this discrete-choice equation:

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

We approximate $\pi_{it} - F_{it}^{0}$ as a reduced-form expression in exogenous firm and market characteristics that are observable in period t:[12]

$$\pi_{it} - F_{it}^{0} = \beta Z_{it} + \mu_t + \mu_i + \omega_{it}.$$

The vector Z_{it} 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 changes 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 (e.g., organizational or managerial ability) that could influence either the level of profits that firms derive from innovations or the cost of innovating; and ω_{it}, a random shock.

[12] This specification follows Roberts and Tybout (1997).

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

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

where $\omega_{it} \sim N(0,1)$. 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 answers (Yes or No) whether the firm introduced any important modification in the production process during year *t*. The second question asks whether the firm manufactured, in year *t*, any brand-new 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 investments included R&D only, WT only, or both activities. This specification also allows us to test for complementarity between both activities, as we will see in the next section.

The rest of the explanatory variables included in the vector Z_{it} control for a set of firm characteristics that are likely to determine the innovation output. *Skilled labor* is a dummy that takes the value 1 if the company has a proportion of skilled workers above the sample average. 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, in its main market, there are at least one but fewer than ten other firms with a significant market share. 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.[13] 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. *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. *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:[14] *Rob/CAD/CAM* takes the value 1 if the firm uses robotics or computer-aided design or computer-aided manufacturing; *NC/FMS* takes the value 1 if the firm uses

[13] 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.
[14] Every four years, the survey questionnaire includes questions on the use of these technologies.

numerical control machines, or flexible manufacturing systems.

High technological opportunities is a dummy variable indicating whether the firm operates in high-tech sectors: Chemical and pharmaceutical products; Machinery and equipment; Computer products, electronics and optical; Electrical material and accessories; Vehicles and accessories; Other transport equipment. This variable captures differences across industries in terms of technological capabilities or opportunities, which are considered to influence both the cost of introducing an innovation and its profitability.

We lag firm characteristics and other 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 for the fact that observations of the same firm are related over time. Second, we estimate a random effects probit model that explicitly controls for firm-unobserved heterogeneity but it does not take into account the correlation of the firm-specific effect with the regressors. That is, we assume that the error term is, $\varepsilon_{it} = \mu_i + \omega_{it}$, where $\omega_{it} \sim N(0,1)$ and $\mu_i \sim N(0, \sigma_u^2)$, and μ_i is uncorrelated with the independent variables. Finally, we use Chamberlain's (1984) random effects probit model; this model allows for 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 unobserved individual heterogeneity depends on the average (over time) of the continuous variables included in vector Z, denoted Z_1: $\mu_i = \lambda_0 + \lambda \overline{Z}_{1i} + a_i$, where $\overline{Z}_{1i}$ is the average of Z_{1it}, t = 1, 2,..., T. We assume further $a_i \sim N(0, \sigma_a^2)$ and $a_i \perp \overline{Z}_{1i}$ (see 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) for the SMEs, under the three different probit models; Table 6B does the same for large firms.[15] 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 probit model and the Chamberlain random effects probit model.

[Insert Table 6A]

The variables of interest are the lagged dummies of investment in R&D and training. According to our specification, we include three dummies: Only R&D; Only WT; Both (R&D and WT). The estimated coefficients for these three variables are significant, which suggests a positive effect of investing in either of these activities. The coefficients increase when we consider fixed firm-specific effects (columns 3 and 4) in comparison with those of the baseline probit model that includes the control variables (column 2). Yet the Chamberlain correction incorporated in column 4 changes the coefficients only slightly when compared to column 3.

The estimated coefficients suggest that firms with past experience in R&D and/or WT

[15] To classify each firm as a small or a large firm, we use the average size of the firm during the whole period. With this criterion, we avoid including a company in different subsamples depending on the year.

are more likely to innovate in the current period, although the magnitudes of the marginal effects (no provided in the tables) are substantially different for the two activities. As expected, experience in R&D has a much greater effect on the likelihood of innovation than does training. The next subsection (5.1) presents the method we use to obtain the marginal effects of these variables and the magnitude of the complementarity.

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 for 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. These results indicate that exporter and multiproduct firms find it more profitable 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). However, we find a no-significant impact of skilled labor.

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

Table 6B provides the estimated coefficients for the subsample of large firms. In this case, on the one hand, the estimated coefficients for the three main variables imply a positive effect of investing in R&D (either simultaneously or separately), but a positive effect of investing in WT only when the firm also invests on R&D. On the other hand, skilled labor and the two variables reflecting the complexity of the production show a significant and positive effect on the probability of innovating, while recessive market has a negative impact.

[Insert Table 6B]

5.1. Analysis of complementarity

In order to estimate the marginal effects of WT and R&D on innovation performance and to identify the existence of complementarity, we need to evaluate how these activities affect the likelihood to innovate when each activity is carried out in isolation as well as when it is added to the other. To do so we first compute for each firm *i* the predicted probabilities using the parameters reported in the fourth column of Tables 6A and 6B for SMEs and large firms, respectively. The probability of innovating when firms have experience in both activities is calculated as

$$P(I_{it} = 1 | R_{it-1} = 1, T_{it-1} = 1, Z_{it}) = P(I_{it} = 1 | 1,1) = \Phi(\hat{\lambda}_{0a} + \hat{\gamma}_{1a} + \hat{\beta}_a Z_{it} + \hat{\lambda}_a \overline{Z}_{1i})$$

where the *a* subscript means that parameters have been multiplied by $(1+\sigma_a^2)^{-1/2}$.

Likewise, the probability when firms have experience only in R&D is computed as

$$P(I_{it}=1|1,0)=\Phi(\hat{\lambda}_{0a}+\hat{\gamma}_{2a}+\hat{\beta}_a Z_{it}+\hat{\lambda}_a \overline{Z}_{1i})$$

while, when they have experience only in WT, as

$$P(I_{it}=1|0,1)=\Phi(\hat{\lambda}_{0a}+\hat{\gamma}_{3a}+\hat{\beta}_a Z_{it}+\hat{\lambda}_a \overline{Z}_{1i})$$

and, finally, when they have no experience in either activity, as

$$P(I_{it}=1|0,0)=\Phi(\hat{\lambda}_{0a}+\hat{\beta}_a Z_{it}+\hat{\lambda}_a \overline{Z}_{1i}).$$

Table 7 reports the averages 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 predicted probability of innovating for SMEs ranges from 21% (in the case of no experience in either R&D or WT) to 46% (in the case of experience in both activities); the respective probabilities range from 36% to 61% for large firms. We also find that all probabilities are higher for firms in high-tech industries than for those in low-tech industries.

[Insert Table 7]

To further illustrate the effect of both investments on the probability of innovating, we have graphed the entire distribution of estimated probabilities for each one of the four possible strategy combinations. Figure 1 shows the corresponding Kernel density functions for SMEs firms (left panel) and large firms (right panel). The position of the Kernel in the case of investing in both R&D and WT indicates higher levels of innovation probability. On the contrary when firms do not have experience in any activity, the probabilities of innovating are the lowest.

[Insert Figure 1]

We use the predicted probabilities to estimate the average marginal effect (*AME*) of each activity when it is undertaken in isolation as well as the effect of adding one activity to the other. The effect of adding R&D when the firm already undertakes WT is calculated as

$$AME_1^R = \frac{1}{N}\sum_i \sum_t [P(I_{it} = 1 | 1,1) - P(I_{it} = 1 | 0,1)]$$

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

$$AME_2^R = \frac{1}{N}\sum_i \sum_t [P(I_{it} = 1 | 1,0) - P(I_{it} = 1 | 0,0)].$$

Similarly it is obtained the effect of adding WT when the firm is already undertaking R&D, $AME_1^T = \frac{1}{N}\sum_i \sum_t [P(I_{it} = 1 | 1,1) - P(I_{it} = 1 | 1,0)]$, and the effect on the probability of innovating due to experience only in WT, $AME_2^T = \frac{1}{N}\sum_i \sum_t [P(I_{it} = 1 | 0,1) - P(I_{it} = 1 | 0,0)]$.

If $AME_1^R \geq AME_2^R$ (and, consequently, $AME_1^T \geq AME_2^T$) we conclude that R&D and WT are two investments that reinforce each other, so there are complementarities between both activities in innovation performance.

Table 8 presents the average marginal effects for SMEs (columns 1-3) and large firms (columns 4-6).[16] The values reported in column 1 suggest complementarity between both activities for SMEs. The second row indicates that, when R&D is added to training, firms increase their probability of innovating by 20.9 percentage points; the increase is smaller (19.8 percentage points) when R&D is carried out in isolation (third row). On average, R&D is more effective when firms have also experience in WT (that is, $AME_1^R \geq AME_2^R$). Although the average magnitude of the complementarity is 1.2 percentage points, it could

[16] The first row shows the average marginal effect of adding both activities when neither of them was present: $AME = \frac{1}{N}\sum_i \sum_t [P(I_{it} = 1 | 1,1) - P(I_{it} = 1 | 0,0)]$.

be determinant for those firms that are very close to becoming innovators.

[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 3.7 percentage points (last row); if WT is combined with existing R&D, that probability increases by 4.8 percentage points.

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

The average marginal effects show some differences for the group of large firms. First, comparing the figures in columns 5 with those in column 6, we can see that the heterogeneity in the magnitude of these effects between high- and low-tech industries almost disappears. Second, complementarity also exists in the group of large firms: adding one investment to the other increases the probability of innovating by 1.8 additional percentage points.

In order to delve more deeply into the analysis of complementarities, Figure 2 plots the firm's marginal effects of training (AME_1^T and AME_2^T) against the probability of innovating for different subsamples, defined according to their R&D and WT status. As we can see in Figure 2A, for SMEs, the effect of training undertaken jointly with R&D is higher than the effect of training in isolation ($AME_1^T > AME_2^T$) for most firms except for those with the highest probability of innovating. This result indicates that worker skills would be more important for those SMEs with greater barriers to innovate. Figure 3 shows the whole distribution of the difference AME_1^T - AME_2^T (the corresponding Kernel density functions) distinguishing between SMEs and large firms. First, the left panel shows that this difference is positive for the vast majority (95.5%) of SMEs. Second, the magnitude of complementarities ranges between 1 and 2 percentage points for most of the SMEs (68%).

Figure 2B presents similar patterns for large firms. The complementarities are present in most of the firms, but decrease as the probability of innovation increases and even disappear for those firms that are highly likely to be innovators (the effect is negative only for the 1.2% of the firms). The right panel of Figure 3 indicates that the magnitude of complementarities ranges between 1 and 3 percentage points for most firms (87%).

In sum, the complementarity effects are more relevant for firms with a low probability of innovating. In fact, the complementarity disappears only when the probability becomes very large. For an appropriate design of the public instruments that promote innovation, it may be relevant to bear this fact in mind.

6. Conclusions

This paper explores the effects of firm R&D and firm sponsored training on innovation performance. Earlier studies have dealt with the effect of R&D and human capital on firm performance without paying much attention to the possible complementarity between these investments. Our study focuses explicitly on the interactions between R&D and WT activities at the firm level and measures their mutual complementarity.

We use a sample of Spanish manufacturing firms over the period 2001-2006 which contains information on the R&D investment, data about investment in worker training, and information on innovation output. The empirical evidence shows important differences between large and small firms in both the frequency of these investments and the likelihood of innovating. For example, 20% of SMEs are engaged in R&D while a higher proportion of them (29%) do innovate. This implies that many SMEs without formal R&D activities are innovators. Firms may rely on activities other than formal R&D to achieve innovation success and worker training may play a relevant role here. In the case of large firms, 71% invest in R&D, but only 55% introduce an innovation. These empirical facts can be related with the existence of heterogeneity in the innovation output or the innovation strategy depending on firm size. For example, large firms might be involved in drastic innovations, while incremental innovations could be more frequent in small firms; large firms might be more engaged in long-term innovation strategies.

To conduct the econometric analysis, we estimate a probit model with a dependent variable that takes the value one when the firm introduced any important modification in the production process or the firm manufactured any brand-new or substantially modified products. The empirical specification considers that firms' experience in R&D and WT can have different effects depending on whether these investments are carried out in isolation or jointly. We include in the model other innovation determinants and take into account the unobserved heterogeneity and the correlation of the firm-specific effect with the regressors. This specification allows us to identify complementarities between R&D and WT. To do so we analyze how the effect of each of these activities on the probability of innovating differs depending on whether or not the company has also invested in the other activity.

The empirical results indicate that R&D is a key factor in explaining firm innovation performance. Worker training investment has a significant effect too, but it is of lower magnitude. In the large firms, WT has a positive impact on the probability only when it is added to R&D, while in the SMEs it has a positive impact also when it is carried out in isolation.

Results confirm that innovation additionally depends on other activities or market-related factors. In the case of SMEs, those that are multiproduct firms in high-tech sectors, open to the international markets, and facing an expansive market situation are the ones that have a higher probability of innovating. In large firms, however, the use of sophisticated production technology and a higher proportion of skilled labor play a relevant role and make them more likely to innovate.

The results reported in this paper establish a complementary relationship: worker training reinforces the effect of R&D on innovation performance.

On the one hand, for SMEs (large firms), on-the-job training increases the likelihood of introducing an innovation by 3.7 (6.1) percentage points when it is carried out in isolation. This effect increases within a range of between 1 and 2 percentage points when it is undertaken jointly with R&D (for large firms, between 1 and 3 percentage points). Although training has a smaller effect on innovating than R&D, it clearly reinforces the effect of R&D.

On the other hand, the magnitude of the complementarities varies with the likelihood of innovating, and it almost disappears when this probability is very high. These results indicate that complementarities are more relevant when firms have more difficulties to innovate.

Public policies that promote firms' R&D investment and public policies that encourage worker training are often not connected. This is currently the case in Spain, where the main instruments are designed by different Ministries. Although the average magnitude of the complementarity effects is not too big, our results highlight that it is importance to consider the complementarities between both types of investments when designing public policies that promote R&D and training. This is particularly so for firms that are less likely to innovate and that are often the firms to which the public aids are mainly addressed.

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Table 1. Training and R&D effort by countries (% of GDP)

	R&D [1]	WT [2]
Finland [a]	3.47	0.43
Sweden [b]	3.40	0.44
United States	2.69	0.39
Denmark [a]	2.58	0.53
Germany	2.53	0.54
Austria	2.51	0.48
Canada [c]	1.96	0.48
Belgium [c]	1.89	0.42
Netherlands [c]	1.81	0.42
United Kingdom [a]	1.77	0.52
Norway	1.59	0.55
Czech Republic [c]	1.48	0.39
Spain	1.27	0.27
Italy [a]	1.17	0.18
Portugal	1.17	0.30
Greece	0.60	0.11

[1] Gross domestic expenditure on R&D as a percentage of GDP (2007).
[2] Total annual labour cost of employer-sponsored non-formal education as a percentage of GDP (2007).
[a] Year of reference 2006. [b] Year of reference 2005. [c] Year of reference 2008.

Source: OECD.

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
SMEs				
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 6A. Innovation Performance. Small and medium firms

	(1) Coefficient (Stand. Err.)	(2) Coefficient (Stand. Err.)	(3) Coefficient (Stand. Err.)	(4) Coefficient (Stand. Err.)
Intercept	-0.921***	-1.256***	-2.133***	-2.380***
	(0.039)	(0.139)	(0.232)	(0.334)
Only R&D$_{t-1}$	0.964***	0.804***	1.008***	0.990***
	(0.093)	(0.097)	(0.123)	(0 123)
Only Training $_{t-1}$	0.324***	0.155*	0.217**	0.210*
	(0.083)	(0.087)	(0.110)	(0.110)
Both (R&D and WT) $_{t-1}$	1.288***	1.011***	1.210***	1.204***
	(0.085)	(0.096)	(0.131)	(0.131)
Skilled labor $_{t-1}$		-0.020	0.006	0.003
		(0.069)	(0.095)	(0.095)
Log total employment $_{t-1}$		0.037	0.118*	0.188*
		(0.040)	(0.063)	(0.114)
Number of competitors $_{t-1}$		0.127**	0.116	0.108
		(0.060)	(0.080)	(0.080)
Log of price cost margin $_{t-1}$		0.005***	0.005*	0.001
		(0.002)	(0.003)	(0.003)
Multiproduct firm $_{t-1}$		0.130	0.244**	0.250**
		(0.092)	(0.124)	(0.124)
Exporter firm $_{t-1}$		0.302***	0.382***	0.379***
		(0.067)	(0.094)	(0.094)
Standardized product $_{t-1}$		-0.059	-0.046	-0.043
		(0.064)	(0.091)	(0.091)
Expansive market $_{t-1}$		0.249***	0.243***	0.240***
		(0.062)	(0.082)	(0.082)
Recessive market $_{t-1}$		-0.008	-0.127	-0.123
		(0.070)	(0.091)	(0.091)
Age		-0.002	-0.001	0.002
		(0.002)	(0.003)	(0.010)
Geographical localization		0.039	0.137	0.134
		(0.064)	(0.101)	(0.101)
Rob/CAD/CAM		0.031	0.101	0.090
		(0.064)	(0.089)	(0.090)
NC/FMS		0.145**	0.285***	0.289***
		(0.078)	(0.107)	(0.107)
High technological opportunities		0.089	0.254**	0.273**
		(0.081)	(0.119)	(0.120)
Year dummies		included	included	included
Number of observations	4790	4790	4790	4790
Log-likelihood	-2520.2	-2447.4	-2092.0	-2088.8
% correctly pred 1's	44.6	58.3	58.2	58.4
% correctly pred 0's	88.0	76.4	75.5	74.6
Pseudo R-squared	0.11	0.13		
σ			1.343	1.343
			(0.072)	(0.072)
ρ			0.643	0.643
			(0.025)	(0.025)

***, ** and * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Table 6B. Innovation Performance. Large Firms

	(1) Coefficient (Stand. Err.)	(2) Coefficient (Stand. Err.)	(3) Coefficient (Stand. Err.)	(4) Coefficient (Stand. Err.)
Intercept	-0.766***	-1.535***	-1.938***	-0.674
	(0.119)	(0.432)	(0.682)	(0.970)
Only R&D $_{t-1}$	0.956***	0.892***	0.861***	0.877***
	(0.151)	(0.152)	(0.217)	(0.218)
Only Training $_{t-1}$	0.265*	0.185	0.196	0.208
	(0.144)	(0.147)	(0.205)	(0.206)
Both (R&D and WT) $_{t-1}$	1.136***	0.988***	1.130***	1.163***
	(0.131)	(0.138)	(0.200)	(0.201)
Skilled labor $_{t-1}$		0.136	0.335***	0.342***
		(0.091)	(0.135)	(0.135)
Log total employment $_{t-1}$		0.124*	0.171	-0.067
		(0.065)	(0.108)	(0.168)
Number of competitors $_{t-1}$		0.041	0.125	0.127
		(0.091)	(0.125)	(0.125)
Log of price cost margin $_{t-1}$		0.004	0.006	0.004
		(0.003)	(0.005)	(0.006)
Multiproduct firm $_{t-1}$		0.040	0.140	0.144
		(0.131)	(0.178)	(0.179)
Exporter firm $_{t-1}$		-0.056	-0.064	-0.024
		(0.164)	(0.251)	(0.252)
Standardized product $_{t-1}$		-0.092	-0.008	-0.012
		(0.093)	(0.145)	(0.146)
Expansive market $_{t-1}$		0.113	0.024	0.020
		(0.081)	(0.110)	(0.110)
Recessive market $_{t-1}$		0.021	-0.259*	-0.264*
		(0.100)	(0.140)	(0.141)
Age		0.001	-0.001	0.007
		(0.002)	(0.003)	(0.010)
Geographical localization		0.038	0.026	0.044
		(0.090)	(0.150)	(0.150)
Rob/CAD/CAM		0.311***	0.479***	0.472***
		(0.099)	(0.141)	(0.142)
NC/FMS		0.064	0.214*	0.210*
		(0.089)	(0.125)	(0.125)
High technological opportunities		-0.093	0.011	-0.007
		(0.096)	(0.161)	(0.162)
Year dummies		included	included	included
Number of observations	2083	2083	2083	2083
Log-likelihood	-1323.6	-1288.9	-1085.7	-1083.6
% correctly pred 1's	84.7	77.1	74.2	73.9
% correctly pred 0's	44.9	57.2	58.0	58.5
Pseudo R-squared	0.08	0.11		
σ			1.460	1.464
			(0.109)	(0.110)
ρ			0.681	0.682
			(0.032)	(0.032)

***, ** and * indicate statistically significant at the 1%, 5% and 10% level, respectively.

Table 7. Average predicted probability of innovation success

	Small and medium firms			Large firms		
	All	High Tech. Industries.	Low Tech. Industries.	All	High Tech. Industries.	Low Tech. Industries
$\frac{1}{N}\sum_i\sum_t P(I_{it}=1 \vert 1,1)$	0.461	0.549	0.435	0.611	0.641	0.593
$\frac{1}{N}\sum_i\sum_t P(I_{it}=1 \vert 1,0)$	0.412	0.499	0.387	0.550	0.581	0.532
$\frac{1}{N}\sum_i\sum_t P(I_{it}=1 \vert 0,1)$	0.251	0.325	0.230	0.406	0.436	0.387
$\frac{1}{N}\sum_i\sum_t P(I_{it}=1 \vert 0,0)$	0.214	0.282	0.194	0.362	0.392	0.344
$\frac{1}{N}\sum_i\sum_t P(I_{it}=1)$	0.270	0.390	0.235	0.538	0.597	0.503
N	4790	1086	3704	2083	778	1305

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

	Small and medium firms			Large firms		
	All	High Tech. Industries.	Low Tech. Industries.	All	High Tech. Industries.	Low Tech. Industries
AME	0.246 (0.028)	0.266 (0.063)	0.241 (0.028)	0.249 (0.014)	0.249 (0.018)	0.249 (0.010)
AME_1^R	0.209 (0.021)	0.224 (0.047)	0.205 (0.022)	0.205 (0.012)	0.204 (0.016)	0.206 (0.008)
AME_2^R	0.198 (0.026)	0.217 (0.062)	0.192 (0.026)	0.188 (0.011)	0.189 (0.013)	0.187 (0.010)
AME_1^T	0.048 (0.003)	0.049 (0.008)	0.048 (0.003)	0.061 (0.005)	0.060 (0.007)	0.062 (0.003)
AME_2^R	0.037 (0.007)	0.043 (0.018)	0.035 (0.006)	0.043 (0.004)	0.044 (0.003)	0.043 (0.004)
Complementarity[1]	0.012 (0.006)	0.007 (0.006)	0.013 (0.005)	0.018 (0.006)	0.016 (0.007)	0.019 (0.006)
N	4790	1086	3704	2083	778	1305

Standard deviation of the *AME* in parentheses
[1]Complementarity is defined as AME_1 - AME_2

Figure 1. Kernel density of predicted probabilities of innovation success
SMEs (left panel) Large firms (right panel)

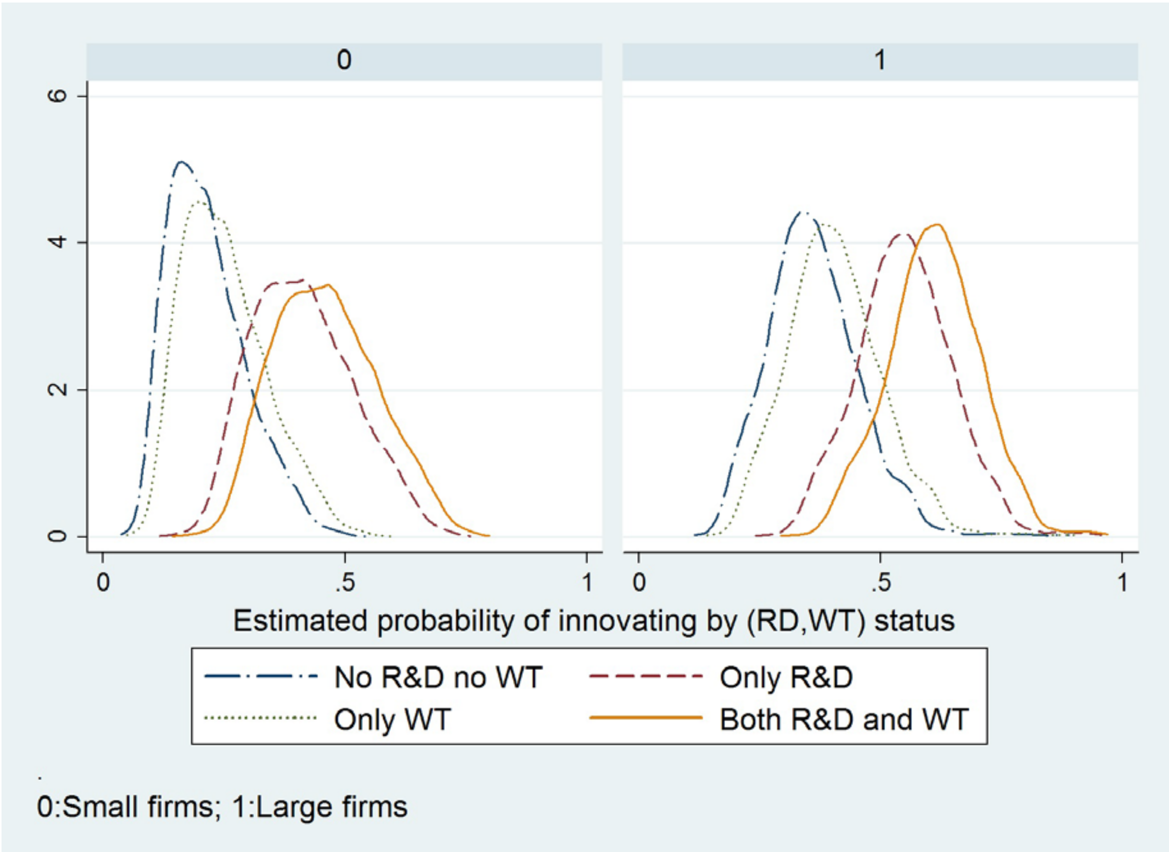


Figure 2A. Average Marginal Effects vs. estimated probability of innovating
(by subsamples, SMEs)

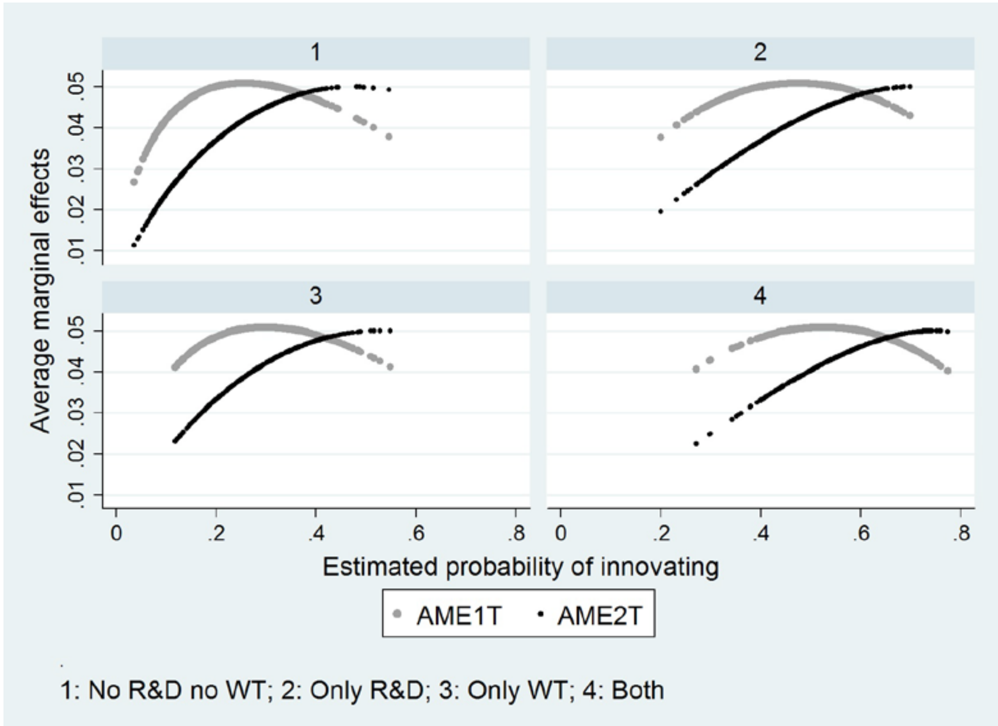


Figure 2B. Average Marginal Effects vs. estimated probability of innovating
(by subsamples, Large Firms)

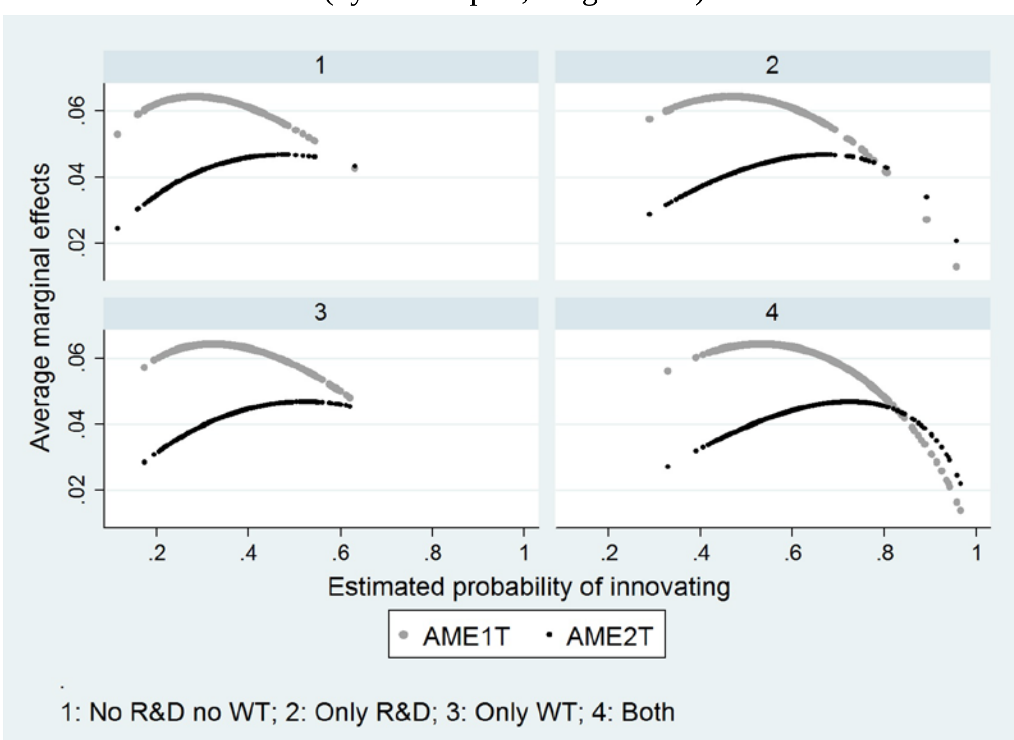
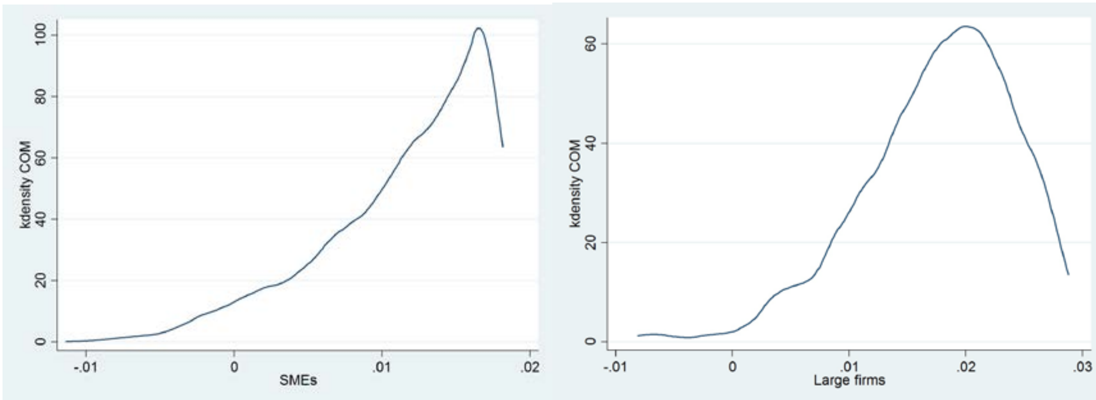


Figure 3. Kernel density of Complementarity (AME_1 - AME_2)

SMEs (left panel) Large firms (right panel)



Appendix A: Variables definition

Innovation	Dummy variable which takes the value 1 if the firm reports that it has introduced at least one (product or process) innovation during the corresponding year. See Section 2 for more details on this variable.
R&D	Dummy variable which takes the value 1 if the firm reports positive (internal or external) expenditures in R&D during the corresponding year. See Section 2 for more details on this variable.
Worker Training (WT)	Dummy variable which takes the value 1 if the firm reports positive external expenditures in worker training (in software and information technology training, in language training, in engineering and technical training, training in sales and marketing, or training in other subjects) during the corresponding year. See Section 2 for more details on this variable.
Total employment	Number of full-time workers plus half the number of part-time workers.
Skilled labor	Dummy variable which takes the value 1 if more than 5% of the employees of the company are white collar workers (engineers, graduates, technical engineers and qualified assistants).
Number of competitors	Dummy variable which takes the value 1 if the firm reports that its main market has between 1 and 10 competitors with a significant market share.
Price cost margin	This variable is approximated by the value of gross output minus the variable costs of production, divided by the value of gross output. The gross output value is computed as sales + stock variation + other revenues. The variable costs of production are obtained as intermediate consumption (raw materials and services) + labor costs. The R&D services have been excluded from cost, and an estimation of the cost of R&D personnel has been deducted from the total labor costs.
Multiproduct firm	Dummy variable which takes the value 1 if the firm reports that it produces more than one product.
Exporter firm	Dummy variable which takes the value one if the firm reports that it exports.
Standardized product	Dummy variable which takes the value one if the firm reports that its products are highly standardized (as opposed to specifically designed for the customers) and that the rivals rarely change their products.
Expansive market	Firms are asked to assess the current and future market situation (slump, stability, or expansion). This variable takes the value 1 if firms answer that the current and future situation in its main market are expansive.
Recessive market	This variable takes the value 1 if firms answer that the current and future situation in its main market are recessive.
Age	The age of the firm is the difference between the year the firm was founded and the current year.

Geographical localization	Dummy variable that takes the value one if the firm is located in one of the three most industrialized regions in Spain: Catalonia, Madrid or Basque Country.
Rob/CAD/CAM	Dummy variable that takes the value one if the firm uses robotics, or computer-aided design (CAD) or computer-aided manufacturing (CAM) technologies.
NC/FMS	Dummy variable that takes the value one if the firm uses numerical control (NC) or flexible manufacturing systems (FMS).
High technological opportunities	Dummy variable that takes the value one if the firm operates in any of these sectors: Chemical and pharmaceutical; Machinery and equipment; Computer products, electronics and optical; Electrical material and accessories; Vehicles and accessories; Other transport equipment.
Time dummies	Set of yearly dummy variables.

Appendix A: Descriptive statistics*

	Small and Medium Firms		Large firms	
	Mean	Max-Min	Mean	Max-Min
Innovation	29.6		54.9	
R&D	21.1		70.8	
Worker Training	24.2		75.8	
Total employment	47.9 (47.5)	2-327	676.8 (1138.1)	62-14,715
Skilled labor	29.6		48.6	
Number of competitors	49.7		71.7	
Price cost margin	8.5 (12.4)	-99.6-73.7	9.4 (11.3)	-80.5-70.6
Multiproduct firm	10.8		13.1	
Exporter firm	50.3		92.9	
Standardized product	57.5		64.3	
Expansive market	22.5		30.4	
Recessive market	19.0		16.0	
Age	21.8 (17.9)	0-165	34.4 (23.7)	0-169
Geographical localization	44.7		50.8	
Rob/CAD/CAM	39.5		70.5	
NC/FMS	17.3		41.8	
High technological opportunities	22.4		37.6	
N (Number of observations)	6686		2886	

[*] For dummy variables, the figures reports the proportion of firms with 1s.
For continuous variables, standard deviation in parentheses.