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

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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 worker training on innovation performance in a sample of Spanish manufacturing firms 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: training reinforces the effect of R&D on innovation performance. The effects differ according to firm size and industry.

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

JEL Classification: D22, L60, M53, O30

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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 national 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). 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." 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] 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

[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.

for Italian and British firms, respectively.[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 (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

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

[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.

activities.

Evidence on the role of training in innovation that is based on Spanish data is scarce. 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, such as training. These authors analyze the differences in this relation depending on the technological level of the industries, yet they do not consider the interactions or complementarities between both types of investment.

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 R&D and training on the likelihood of innovating. In analyzing this relationship, we focus on 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.

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 a relevant issue for policy makers to identify the existence of complementarities.

[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.

The results suggest a degree of complementarity between both activities. In small and medium firms, R&D increases the probability of innovating by 25.5 percentage points when it is carried out in isolation; while, when R&D is added to training, the probability of innovating increases by 29 percentage points. Training also increases the probability but, to a lesser extent: by only 3.9 percentage points, when it is carried out in isolation; by 7.4 percentage points, when it is added to R&D. 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. Section 4 describes the empirical strategy and Section 5 reports the results. Section 6 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 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 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 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 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.[6] 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 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 abstinence 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.

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

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 8), an interesting point 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 relevant regularity is, 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 all sample 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,[7] 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 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 innovating, F_{it} (subscripts i and t index firms and time, respectively):

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

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

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.

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. Because 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 $t-1$:[8]

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

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 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

[8] Mañez *et al.* (2009) analyze the existence of sunk R&D costs associated with performing R&D. They find that past experience in R&D influence current decision to invest in R&D.

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 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:

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

We approximate $\pi_{it} - F_{it}^0$ as a reduced-form expression in exogenous firm and market characteristics that are observable in period t:[9]

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

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

[9] This specification follows Roberts and Tybout (1997), who develop a model of export-market participation in the presence of sunk costs.

derive from innovations or the cost of those innovations; and ω_{it}, an unobserved shock. The latter term can be viewed as the random shock (or uncertainty in the innovation processes) that is not observed by the econometrician but may affect the firm's decision to innovate in a given year.

Our goals are to identify 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) pairing in the previous period (this assumption will later 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:

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

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. We can test the null hypothesis –that investments in R&D and WT have 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} 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, 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.[10] 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:[11] *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 numerical control machines, or flexible manufacturing systems.

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 captures differences across industries in terms of technological capabilities or opportunities, which are considered to influence both the cost of innovation

[10] 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.

[11] The survey questionnaire includes questions on the use of these technologies every four years

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 firms are related over time.

Second, we assume that the error term is, $\varepsilon_{it} = \mu_i + \omega_{it}$, where $\omega_{it} \sim N(0,1)$ and $\mu_i \sim N(0, \sigma_u)$, 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 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 time-averaged 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 $a_i \sim N(0, \sigma_a)$ 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. 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. 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.

The estimated coefficients 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 (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 (see section 5.1 for details).

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).

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). 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, only three of the control variables show a significant effect on the probability of innovating: recessive market has a negative impact, while the two variables reflecting the complexity of the production have a positive impact.

[Insert Table 6B]

5.1. Analysis of complementarity.—

In order to estimate the impacts of WT and R&D on the likelihood of innovating, for each firm i, we first compute 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

$$P(I_{it} = 1|\ R_{it-1} = 1, T_{it-1} = 1, \widehat{\beta} Z_{it}) = P(I_{it} = 1|\ 1, 1) = \Phi(\widehat{\alpha} + \widehat{\gamma}_1 + \widehat{\beta} Z_{it}).$$

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

$$P(I_{it} = 1|1, 0) = \Phi(\widehat{\alpha} + \widehat{\gamma}_2 + \widehat{\beta} Z_{it}),$$

while, when they have experience only in WT, as

$$P(I_{it} = 1|0, 1) = \Phi(\widehat{\alpha} + \widehat{\gamma}_3 + \widehat{\beta} Z_{it}),$$

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

$$P(I_{it} = 1|0,0) = \Phi(\widehat{\alpha} + \widehat{\beta} Z_{it}).$$

Table 7 reports the averages of these predicted probabilities 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 11% (in the case of no experience in either R&D or WT) to 44% (in the case of experience in both activities); the respective probabilities range from 27% to 68% 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]

We use the predicted probabilities to estimate the average marginal effect 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

$$AME_1^R = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it} = 1|1,1) - P(I_{it} = 1|0,1)] = \frac{1}{N}\sum_{i=1}^{N}[\Phi(\widehat{\alpha}+\widehat{\gamma}_1+\widehat{\beta} Z_{it}) - \Phi(\widehat{\alpha}+\widehat{\gamma}_3+\widehat{\beta} Z_{it})]$$

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

$$AME_2^R = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it} = 1|1,0) - P(I_{it} = 1|0,0)] = \frac{1}{N}\sum_{i=1}^{N}[\Phi(\widehat{\alpha}+\widehat{\gamma}_2+\widehat{\beta} Z_{it}) - \Phi(\widehat{\alpha}+\widehat{\beta} Z_{it})].$$

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, respectively, as $AME_1^T = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it} = 1|1,1) - P(I_{it} = 1|1,0)]$ and $AME_2^T = \frac{1}{N}\sum_{i=1}^{N}[P(I_{it} = 1|0,1) - P(I_{it} = 1|0,0)]$.

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 exist complementaries between both activities in innovation performance.

Table 8 presents the average marginal effects. 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 29 percentage points; the increase is smaller (26 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, $AME_1^R \geq AME_2^R$).

[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 the average marginal effects computed separately for the subsamples of firms 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 greater for low-tech industries.

These general patterns are similar for the group of large firms, although we can point out two differences. First, 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. Second, the heterogeneity in the magnitude of these effects between industries 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 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 it also provides 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, by analyzing if the effect of each of these activities on the probability of innovating varies depending on whether the company has also invested in the other one or not.

The empirical results indicate 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. 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. In addition, results confirm that innovation in SMEs also depends on other activities or market related factors, while for large firms formal R&D activities are more determinant.

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 lower for the latter. Lastly, complementarity seems to be greater in low-tech industries.

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. Our results highlight the importance of considering the complementarities between both types of investments in the design of public policies that promote R&D and training.

References

Arora, A. and A. Gambardella (1990), "Complementarity and external linkages: the strategies of the large firms in biotechnology," *The Journal of Industrial Economics,* 38(4), 361–379.

Bartel, A. (1994), "Productivity gains from the implementation of employee training programs," *Industrial Relations*, 33(4), 411–425.

Bartel, A. (1995), "Training, wage growth, and job performance: evidence from a company database," *Journal of Labor Economics*, 13(3), 401–425

Bartel, A. (2000), "Measuring the employer's return on investments in training: evidence from the literature," *Industrial Relations,* 39(3), 502–524.

Bartel, A. and Lichtenberg, F. (1987), "The comparative advantage of educated workers in implementing new technologies," *The Review of Economics and Statistics*, 69(1), 1–11.

Ballot, G., F. Fakhafakh and E. Taymaz (2001), "Firms' human capital, R&D and performance: a study on French and Swedish firms," *Labour Economics*, 8(4), 443–462.

Ballot, G., F. Fakhafakh and E. Taymaz (2006), "Who benefits from training and R&D: the firm or the workers?," *British Journal of Industrial Relations* 44(3), 473–495.

Becheikh, N., L. Réjean, N. Amara (2006), "Lessons from innovation empirical studies in the manufacturing sector: a systematic review of the literature from 1993–2003," *Technovation*, 26, 644–664.

Bassanini, A., Booth, A., Brunello, G., De Paola, M., Leuven, E. (2005), "Workplace training in Europe," IZA Discussion Paper n^{o}1640.

Black, S. E. and L.M. Lynch (1996), "Human-capital investments and productivity," *The American Economic Review*, 86(2), 263–267.

Blundell, R., Dearden, L., Meghir, C. and Sianesi, B. (1999), "Human capital investment: The returns from education and training to the individual, the firm and the economy," *Fiscal Studies* 20 (1), 1–23.

Bresnahan, T.F., E. Brynjolfsson and L. M. Hitt (2002), "Information technology, workplace reorganization, and the demand for skilled labor: firm-level evidence," *The Quarterly*

Journal of Economics, 117(1), 339-376.

Cassiman, B. and R. Veugelers (2006), “In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition,” *Management Science,* 52(1), 68–82.

Chamberlain, G. (1984), “Panel data,” in: Z. Griliches and M. D. Intriligator (Eds.), *Handbook of Econometrics*, Volume 2, 1247–1318, Amsterdam: North Holland.

Cohen, W. M. and D. A. Levinthal (1989), “Innovation and learning: the two faces of R&D,” *The Economic Journal*, 99, 569–596.

Conti. G. (2005), “Training, productivity and wages in Italy,” *Labour Economics*, 12(4), 557-576.

Dearden, L., H. Reed and J. Van Reenen (2006), “The impact of training on productivity and wages: evidence from British panel data,” *Oxford Bulletin of Economic and Statistics*, 68(4), 397–421.

Gallié, E.-P. and D. Legros (2012), “Firms’ human capital, R&D and innovation: a study on French firms,” *Empirical Economics*, 43(2), 581-596.

Griliches, Z. (1998), *R&D and Productivity: The Econometric Evidence*, University of Chicago Press, Chicago.

Griffith, R., S. Redding and J. Van Reenen (2004), “Mapping the two faces of R&D: productivity growth in a panel of OECD industries,” *The Review of Economics and Statistics*, 86(4), 883–895.

Hall, B. H., (2011), “Innovation and productivity,” NBER Working Paper n^o 17178.

Hall, B. H., J. Mairesse and P. Mohnen (2010), “Measuring the returns to R&D,” in: B. H. Hall and N. Rosenberg (Eds.), *Handbook of the Economics of Innovation*, North-Holland, Amsterdam.

Huergo E. and L. Moreno (2011), “Does history matter for the relationship between R&D, innovation, and productivity?,” *Industrial and Corporate Change*, 20(5), 1335–1368.

Laursen, K. and N. Foss (2003), “New human resource management practices, complementarities, and the impact on innovation performance,” *Cambridge Journal of Economics*, 27(2), 243–263.

Leiponen, A. (2005), “Skills and innovation,” *International Journal of Industrial Orga-*

nization, 23(5–6), 303–323

Máñez, J. A., M. E. Rochina-Barrachina, A. Sanchís and J. A. Sanchís (2009), "The role of sunk cost in the decision to invest in R&D," *The Journal of Industrial Economics,* 57(4), 712–735.

Milgrom, P. and J. Roberts (1990), "Rationalizability, learning and equilibrium in games with strategic complementarities," *Econometrica,* 58(6), 1255–1277.

Milgrom, P. and J. Roberts (1995), "Complementarities and fit: strategy, structure and organizational change in manufacturing," *Journal of Accounting and Economics,* 19, 179–208.

Miravete, E. J. and J. C. Pernías (2006), "Innovation complementarity and scale of production," *The Journal of Industrial Economics,* 54(1), 1–29

Mohnen P. and L.-H. Röller (2005), "Complementarities in innovation policy," *European Economic Review*, 49(6), 1431–1450.

Nelson, R. R. and E. Phelps (1966), "Investment in humans, technological diffusion, and economic growth," *The American Economic Review*, 56(1/2), 69–75.

OECD (2005), *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data,* *3*rd edition. OECD Publishing, Paris.

OECD (2010), "Ministerial report on the OECD Innovation Strategy," OECD Publishing, Paris [online]. Available: http://www.oecd.org /site/innovationstrategy/

Rammer, C., D. Czarnitzki, and A. Spielkamp (2009), "Innovation success of non-R&D-performers: substituting technology by management in SMEs," *Small Business Economics,* 33, 35–58.

Roberts, M. J. and J. R. Tybout (1997), "The decision to export in Colombia: an empirical model of entry with sunk costs," *The American Economic Review,* 87, 545-64.

Rogers, M. (2004), "Networks, firm size and innovation," *Small Business Economics*, 22, 141–153.

Santamaría, L., M. J. Nieto and A. Barge-Gil (2009), "Beyond formal R&D: taking advantage of other sources of innovation in low- and medium-technology industries," *Research Policy,* 38, 507–517.

Zhou, H., R. Dekker and A. Kleinknecht (2011), “Flexible labor and innovation performance: evidence from longitudinal firm-level data,” *Industrial and Corporate Change,* 20(3), 941-968.

Wooldridge, J. (2001), *Econometric Analysis of Cross Section and Panel Data,* Cambridge, MA: MIT Press.

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	-0.922*** (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)
Standardized 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)
NC/FMS 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)

***, ** 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	-0.770*** (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)
Standardized 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)
NC/FMS 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)

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

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.
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,1)]$	0.435	0.574	0.394	0.682	0.723	0.658
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|1,0)]$	0.361	0.496	0.322	0.577	0.622	0.550
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|0,1)]$	0.145	0.234	0.119	0.342	0.387	0.315
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\|0,0)]$	0.106	0.178	0.085	0.265	0.307	0.240
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1)]$	0.187	0.343	0.141	0.560	0.649	0.507
N	4799	1089	3710	2086	779	1307

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.
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\vert 1,1)-P(I_{it}=1\vert 0,0)]$	0.328	0.395	0.309	0.417	0.416	0.417
	(0.09)	(0.06)	(0.09)	(0.05)	(0.06)	(0.04)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\vert 1,1)-P(I_{it}=1\vert 0,1)]$	0.290	0.340	0.275	0.340	0.336	0.342
	(0.07)	(0.05)	(0.07)	(0.04)	(0.05)	(0.03)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\vert 1,0)-P(I_{it}=1\vert 0,0)]$	0.255	0.318	0.237	0.312	0.316	0.309
	(0.08)	(0.06)	(0.08)	(0.04)	(0.05)	(0.04)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\vert 1,1)-P(I_{it}=1\vert 1,0)]$	0.074	0.077	0.073	0.105	0.100	0.108
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
$\frac{1}{N}\sum_{i=1}^{N}[P(I_{it}=1\vert 0,1)-P(I_{it}=1\vert 0,0]$	0.039	0.055	0.034	0.077	0.081	0.075
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	4799	1089	3710	2086	779	1307

Standard deviation of the AME in parentheses