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UNDERSTANDING THE SPANISH BUSINESS INNOVATION GAP: THE ROLE OF SPILLOVERS AND FIRMS' ABSORPTIVE CAPACITY*

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CORPORATE R&D: AN ENGINE FOR GROWTH, A CHALLENGE FOR EUROPEAN POLICY

The link between corporate R&D, innovation, and employment

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Abstract

This paper investigates whether the existence of knowledge spillovers, differences in the capacity of firms to assimilate them and disparities in some human resource management practices affect the decision to innovate in Spanish firms during the period 2003-2007. In order to do this, we employ data from the "Central de Balances" database, which covers both manufacturing and services firms, and use an estimator proposed by Wooldridge (2005) for dynamic random effects discrete choice models. The empirical exercise provides evidence on the positive effect of spillovers on the innovative behaviour of companies, not just for the knowledge generated in the same industry, but also for that generated in the same region or by the public sector. Moreover, these effects are enhanced for those firms with a higher capacity to absorb those spillovers. This ability is a function of firms' R&D capabilities, but also of such factors as the quality of the labour force, the share of temporary employment and the amount of resources spent in training. In addition to these factors, we have found that innovation performance exhibits true state dependence. Further, some other observed firm characteristics, such as size, sales growth, export behaviour, sector capital intensity or financial structure variables, are also found to be relevant determinants of the likelihood of innovation.

Key words: innovation, R&D, spillovers, absorptive capacity, skilled labour, temporary employment, dynamic RE probit model

JEL classification: O32, C23, C25, J6, J24, L00

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1 - Introduction

There is a widespread consensus that globalisation and the increasing importance of the Information and Communication Technologies (ICT) have substantially changed the economic landscape across the world. This profound transformation, along with the incorporation of emerging market economies to international trade, has undermined the competitiveness of European countries in the global stage. In response to this situation, the European Council launched the Lisbon Agenda in 2000 with the strategic objective of transforming Europe into the most competitive and dynamic economy of the world by 2010. In order to achieve such an ambitious target, reforms were proposed in five different policy areas, most importantly, in the development of the new knowledge economy, where the role of R&D investment was deemed as crucial, a dimension in which some countries, Spain among them, have been lagging behind.[1]

Given this challenging starting point, Spain has made a substantial effort to catch up with the rest of Europe in terms of innovation and technology progress, increasing public funding for civilian R&D activities by 25% on average every year between 2004 and 2008. The result is that the gap in *public* R&D spending between Spain and its European peers disappeared in 2008. The gap in *private* R&D spending continues to be, however, very large: 0.6% of GDP in Spain against 1.2% in EU15 and 1.9% in the US. Moreover, according to a very recent European Commission publication,[2] only 21 Spanish companies are included in the ranking of the 1000 European firms that invest the most in R&D, and their combined R&D spending amounts barely to 1% of the total private R&D spending within the EU.[3] These figures compare poorly with the 247 British firms in the ranking, which represent together about 15% of total private R&D in the EU, 209 German ones, which account for more than one-third of R&D, or the 70 Swedish firms accounting for 5% of total EU R&D.

This paper shows that the Spanish innovation system is paying a double toll for this deficit in terms of private sector R&D spending: on the one hand, the lack of independent R&D effort is affecting directly the capacity of private firms to innovate; on the other hand, it is diminishing their capability to benefit from spillovers generated by knowledge produced elsewhere, that is, it is affecting firms' absorptive capacity (Cohen and Levinthal 1989, and Geroski 1995). The role of independent R&D effort to enhance the capacity to absorb and incorporate knowledge generated elsewhere into the production process of a firm – whether generated by other firms in the same sector of activity or in the same region, or by the public sector–, has already been well documented (see, for example, Jaffe 1986). We find that, in the case of Spain, the marginal benefit of knowledge spillovers on a firm's probability of innovation increases six-fold when the firm carries out its own R&D activity, as compared to a firm with no R&D spending. That is, the observed private R&D underinvestment could be undermining the innovative capabilities of Spain more than previously believed, as well as decreasing the return on public R&D investment.

The second contribution of the paper is more general, although it has important implications for the particular case of Spain. We show that a firm's absorptive capacity depends crucially on its human capital, which we understand in a broad sense here. More

[1] According to the OECD, in 1999 only 0.9% of GDP was devoted to R&D in Spain, vis-à-vis 1.9% in the EU15 and 2.6% in the US.
[2] "The 2009 EU Industrial R&D Investment Scoreboard".
[3] Furthermore, 40% of that was due to the R&D spending of only one firm, telecommunications company Telefónica.

concretely, we find that the skill composition of the workforce and the provision of on-the-job training increase the probability of being innovative not directly, but because they raise the capacity of a firm to benefit from technology spillovers stemming from a third party. The use of fixed-term contracts, on the other hand, seems to directly affect the innovation performance of a firm, as it has been proven elsewhere, possibly due to the low motivation and training possibilities of employees on temporary contracts.[4]

The idea that human capital might enhance a firm's ability to absorb external knowledge is not new. Cohen and Levinthal (1990 and 1994), for instance, argue convincingly that the absorptive capacity of a firm is the by-product of three factors: its R&D activities, its production experience and, lastly, its personnel technical training. Hall and Mairesse (2006) argue persuasively that the technical training of the employees or other human resource management decisions are important for innovation because a firm's knowledge is embedded in the human capital of its employees. Hence, the capacity of the company to understand and incorporate knowledge produced elsewhere will depend not only on its spending on R&D, but also on the expertise and know-how of its personnel. Bartel and Lichtenberg (1987) confirm this view finding that highly educated workers have a comparative advantage with respect to the adjustment and implementation of new technologies. Vinding (2006) finds as well that updating the skills of the employees is crucial for innovation in technology-advanced sectors.

There is some empirical evidence that supports the importance of human capital as a determinant of the absorptive capacity of spillovers at the country level. Coe, Helpman and Hoffmaister (1997), Engelbretcht (1997), Frantzen (2000) and Griffith et al (2004), for example, relate a country's TFP growth with its exposure to international technology spillovers and its capacity to benefit from them, proxied by own R&D and the qualification of the labour force.[5] At a firm level, however, the role played by the quality of the labour force to determine the absorptive capacity is much less documented. Vinding (2006) and Ramijn and Albalejo (2002) are two of the few papers exploring this issue. They find that firms with more qualified personnel, as well as with up-to-date technical skills, are more innovative and argue that this is the result of the role of human capital as enhancer of a firm's absorptive capacity of external knowledge. However, they fail to include an interaction term between the firm's human capital and the spillover pool in the regression in order to quantify the amplifying effect of the variable.[6]

In short, we estimate a dynamic random effects probit model –which allows to control for unobserved heterogeneity, for endogeneity and to handle the initial conditions problem–, using a new database resulting from the combination of detailed firm-level information for a sample of Spanish firms compiled by the Bank of Spain and a survey on firms' innovative activities managed by the Spanish National Statistic Institute. The purpose of this exercise is to compute a sort of total effect of the Spanish business sector low investment in R&D upon the Spanish firms' innovation performance. The total effect would include the direct effect on the innovation capacity of firms –which we relate to the presence of true state dependence– as well as the indirect effect due to their lower capacity to absorb knowledge spillovers. We then proceed to broaden the concept of absorptive capacity and make it dependent on human capital variables, such as the qualification of the workforce, the

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[4] See for example the work of Michie and Sheehan (1999 and 2003).
[5] All four papers find that countries further from the technology frontier catch up faster the more educated their labourforce. The reason is that they are able to benefit to a greater extent from technology spillovers stemming from the more advanced countries.
[6] As proposed by Cohen and Levinthal (1989) in their seminal paper.

provision of on-the-job training or the use of temporary contracts. We allow those variables to enter directly and indirectly, affecting the firm's absorptive capacity of external knowledge, in the regression.

We also study the role played by spillovers generated by different types of knowledge capital. Hence, we proxy the stock of external knowledge –in other words, the spillover pool– by the R&D capital stock of firms operating in the same sector of activity or region, giving therefore some information as on whether sector or regional spillovers are more important, and the R&D capital stock generated by the public sector. We find that they are all relevant for the decision to innovate.

Given the fact that Spanish firms are not only lagging behind R&D spending, but also in most of those human resource practices studied here,[7] these results have important policy implications. In order to change the Spanish productive system from one based on low productivity activities, such as construction and tourism, to one based on knowledge and innovation it will not be enough to devote large quantities of public resources to R&D; policy-makers would have to make sure as well that Spanish firms are able to benefit from that effort.

The next section reviews briefly the literature on spillovers and absorptive capacity of firms. Section 3 describes the database used in the paper. Section 4 explains in detail the empirical methodology and variables included in the analysis and section 5 presents the econometric results. Finally, section 6 concludes.

2 - Literature review

This paper explores the determinants of the innovation performance of firms and, therefore, it takes some elements of the methodological framework from the seminal paper of Crépon *et al.* (1998). However, the main focus of the paper is on the role played by spillovers and their interaction with the absorptive capacity of a firm. The impact of knowledge spillovers has remained the primary focus of research in economic growth since the work of Romer (1990) and Aghion and Howitt (1992) on endogenous growth models. In this type of models, the main input of the aggregate knowledge production function, assumed to have constant returns to scale (CRS), is research and development. Hence, more R&D leads to an increasing economic growth rate. The CRS assumption has been extensively confirmed at the aggregate level (see Griliches 1990 and Jaffe and Trajtenberg 2002). However, micropanel evidence persistently shows diminishing returns to scale (see Hall *et al.* 1986 and Blundell *et al.* 2002). Griliches (1979) reconciles both observations, the existence of CRS in the knowledge production function at the aggregate level and DRS at the firm- or industry-level, by means of the existence of knowledge spillovers: one firm's R&D efforts may contribute positively to another firm's innovation performance.

[7] According to the OECD Main Science and Technology Indicators and Eurostat, the temporary rate in Spain triples that in other European countries and the percentage of firms which provide on-the-job training is about 15pp below that in EU25 and almost half of that in the UK. Further, the percentage of skilled workers (persons with at least secondary education) is 10pp lower than in France and the UK (44% against 65% and 69%, respectively), and almost half of that in Germany.

The existence of knowledge spillovers, estimated to be quite large by, for example, Jaffe (1986),[8] is very relevant for the discussion on the need, or the lack thereof, of public intervention to foster innovative activities. Common wisdom is that knowledge is a public good, that is, it is non-rival and non-excludable. Hence, a firm investing in knowledge has no means to appropriate the returns from that investment, which would discourage research activities. Moreover, as pointed out by Mansfield et al (1981), the cost of imitating research done by other firms is much lower than the cost of generating original research.[9] The result of this difference between the private and social R&D return is an underinvestment in knowledge generation. In this context, public intervention would be justified to, among other things, increase appropriability –through the patent system. However, too much appropriability reduces spillovers and, according to Spence (1984), could result in an incorrect pricing of R&D results. The reason is that full appropriability would deter one firm from building on the research done by other firms. Hence, there would be an overinvestment in overlapping R&D activities. The result would be that innovation is achieved at a too high cost.

However, according to Geroski (1995), the existence of a dilemma between the negative incentive effect of spillovers and their positive impact on other firms' innovation outcomes is not such if one takes into account the fact that, in order to benefit from spillovers, firms have to undertake their own R&D. That is, if one takes into account the double face of R&D, in Cohen and Levinthal (1989) wording, both as a direct innovation determinant and as an indirect promoter of one firms' capacity to absorb, understand and include into its own production process research done by another party, spillovers do not have necessarily to result in less private R&D (see Bernstein and Nadiri 1989).

The role of independent R&D as the driver of the ability of a firm to acquire and make use of the R&D activities of others, that is, to take full advantage of knowledge spillovers, has been most convincingly pushed forward by Cohen and Levinthal (1989) and Geroski (1995) in a microeconomic context. At an aggregate level, Griffith *et al.* (2003, 2004) propose and test a theoretical model of technological transfer which encompasses endogenous growth and the dual role of R&D, to produce innovation and to assimilate others' discoveries. One of the main implications of their model is that the social rate of return of R&D will be underestimated unless its role to promote absorptive capacity is taken into account. Jaffe (1986) estimates quantitatively a patent/profit equation at the firm level where the explanatory variables are the size of the spillover pool and its interaction with the firm's own R&D effort finding a large direct effect of spillovers. He also finds that, given a certain spillover pool, firms with more R&D spending benefit more from it. Also at a firm level, Levin *et al.* (1987) survey a sample of US firms to explore how firms do actually protect their inventions and learn about others innovations. On average, independent R&D was ranked as the most effective means of learning about rival technology.[10]

However, R&D spending is by no means the only determinant of a firm's absorptive capacity. On a theoretical level, Acemoglu (2007) argues that, due to the complementarities between technology and workforce skills, if the job turnover rate increases –for instance, due to a high prevalence of temporary employment–, then the firm does not invest in new technology or on-the-job training for workers, because the

[8] Jaffe (1986) estimates that if all firms increased R&D spending by 10%, total patents would increase by 20% with more than half the increase coming from a pure spillover effect.

[9] He estimates that on average imitation costs are about 65% of the original innovation costs.

[10] In the context of productivity analysis, Harhoff (2000) and Beneito (2001) *inter alia* find evidence in favour of spillover effects rising with R&D to sales ratios, which would be in line with the absorptive capacity hypothesis.

additional return on training or on R&D would benefit a worker who will probably soon leave the firm and benefit a rival company with its knowledge. Further, if workers do not expect firms to invest in new technology or in training, then their wages may not be high enough for them to invest in human capital accumulation. Empirically, at a country level, Guellec and van Pottelsberghe (2004) use a panel of 16 countries to estimate their respective TFP growth elasticity to business, public sector and foreign stocks of R&D and explore the role of a country's absorptive capacity to explain observed differences. They find that both countries' independent R&D and education levels can explain most of the estimated differences. Using a similar framework, but data for both developed and developing countries, Bosch *et al.* (2005) find that the gap in the elasticity of patent counts to R&D found between this two types of countries can be fully explained by differences in patenting protection legislation and education, which enters as a determinant of a country's absorptive capacity. Along these same lines, Eaton and Kortum (1996) fit OECD data to a growth model of technology diffusion to find that a country´s level of education significantly facilitates its ability to adopt foreign technology.

Other aspects weakly related to a firm's human capital, such as flexible work practices or human resource management techniques, have also been found to significantly affect firms' innovation performance. Grabowski (1968) was the first to claim that temporary hiring and firing of researchers might be particularly costly in innovating firms. The first reason is that the supply of researchers is relatively inelastic, which increases the adjustment cost of the workforce in innovative firms. The second reason is that, if fired, employees can transfer part of the firm's knowledge to a competitor. Much more recently, Michie and Sheehan (1999, 2003) have estimated using a sample of UK firms that several human resource practices, the extensive use of fixed-term contracts among them, have an important direct impact on the innovative capacity of firms. One of the possible reasons for this result is provided in Albert *et al.* (2005), who find that workers on temporary contracts have a lower probability of receiving on-the-job training, because firms are less interested in investing in specific human capital due to higher turnover rates. Also, temporary employees may be intrinsically less "effective" (or less qualified) and could suffer from lack of motivation as they have low chances to become permanent employees (Dolado and Stucchi 2008). In the context of an innovative firm this could bear an important cost in terms of firm's performance.

However, as far as we can see there is no paper that explores whether this type of human resource practices have as well an impact on firms' absorptive capacity. That is, whether their actual impact on innovation is underestimated due to the omission of one of the channels of transmission, as it happens in the case of independent R&D.

3 - The database

In this paper we use firm-level information from the "Central de Balances" (CB) of the Bank of Spain. Since 1983, the CB has been compiling and publishing aggregate information of collaborating firms' balance sheets in order to follow the economic situation of the private non-financial Spanish sector. The information is provided on voluntary grounds every year by a substantial number of established companies, about 9000 non-financial firms in 2007.[11] Collaborating firms fill a questionnaire with detailed accounting information, as well

[11] Self-employed are not included. In 2007, about 50% of collaborating firms were Corporations and 45% Limited Liability Companies. The rest were mainly cooperatives.

as some other additional information –of great interest for our study– such as employment, skilled composition of the workforce, type of contracts, training spending or, since 1991, R&D expenditures. The information for the current and the previous period is provided every year to improve the quality of the data and reduce missing points. Moreover, about 75% of firms are re-contacted to clarify some datum or fill in gaps, and more than 200 basic quality controls are run on a routine basis. Hence, the quality of the data is outstanding.

On the negative side, the selection of firms does not intend to be representative of the population, but rather depends on their voluntary cooperation with the Bank. This implies that some sectors are better represented than others. Particularly, as one can see in Table 1, the energy sector is very well covered, with a value-added coverage rate of over 70%. Industry and market services –especially trade, post, transport and telecommunications–, are quite well covered: collaborating firms account for about 30% of value added and about 20% of total employment in industry, and 20% and about 23%, respectively, in the market service sector. On the other hand, agriculture, mineral extraction and construction (grouped under “other”) have a less than 10% coverage rate, both in terms of value added and employment.[12] Another important source of bias is the larger-than-average size of collaborating firms. In the industry sector, for example, about 50% of firms in the sample had less than 250 employees, against more than 95% in the population. Lastly, the geographical location of firms is assigned according to the fiscal address of headquarters. Hence, the coverage rate in Madrid, the Basque Country and Catalonia is larger than that in other regions, amounting to 60%, 23% and 20%, respectively.

For the current study we use three different samples of firms (Table 2). The first one, labeled the “extended” sample, is an *unbalanced* panel for about 2,500 firms during the period 1991-2007. The only requirement for a firm to be in this sample is to remain, at least, four consecutive years in it. The second sample is labeled the “restricted” sample. It is a *balanced* panel of almost 800 firms spanning from 2002 to 2007; hence, each firm has 6 years of information. Lastly, the third sample is labeled “CB-PITEC” and results from merging the CB dataset with the PITEC database. PITEC (*Panel de Innovación Tecnológica*) is a panel of firms managed by the National Statistics Institute, the Spanish Foundation for Science and Technology and COTEC containing detailed information about innovation outputs and inputs, as well as other related information, for the period 2003 to 2007.[13] The panel includes more than 70% of all Spanish firms with 200 employees or more (one-third of those large firms perform innovative activities) and a sample of firms with less than 200 employees with a substantial bias in favor of firms performing innovative activities. Using the firms’ fiscal identification number, we were able to incorporate some relevant information –more on this below– provided by PITEC to about 500 firms of our dataset during the period 2003-2007.

Table 2 shows the percentage of innovating firms in each of the samples, as well as other characteristics, such as the sector and size distribution.[14] The restricted sample retains

[12] Firms are classified into the different economic sectors according to their main activity.

[13] For more information on PITEC and access to aggregate data, refer to the webpage http://sise.fecyt.es.

[14] Note that during the period of analysis some firms moved across sectors, regions, sizes, etc. More concretely, referring to the extended sample of 2,565 firms, about 7% of them changed at least once of sector of activity (2% more than once), 0.6% changed of region and 25% varied of size at least once (defined broadly as SMEs or large firms). We decided to keep those firms in the sample and assign to each of them every year their corresponding sector, size, etc. Lastly, about 20% of the firms in the extended sample have gone through at least one change in ownership, due to mergers or divisions. We have marked those firms and kept them in the sample only if we could follow them after the change.

30% of firms from the extended sample, with the same share of innovative firms (25%). In addition, the restricted sample is similar to the extended one in terms of the sector distribution as well as in other relevant characteristics, such as the export share o the portion of firms quoted in a stock market. On the other hand, it increases somewhat the bias towards larger firms. As regards the CB-PITEC sample, it loses one year and 40% of firms with respect to the restricted sample. Besides, it has 10 percentage points more innovators, but a similar sector distribution, which is a bit biased towards industrial firms. The size bias worsens, as well as the bias towards exporting firms. All in all, these samples are deemed to be reasonably similar.

Table 3 shows the detailed sector distribution and percentage of firms with positive R&D spending in 25 sectors of activities in all the 3 samples. Finally, Table 4 shows the regional distribution of observations across the 3 samples. Overall, the sector and regional distribution of firms is reasonably similar across samples, while there are more differences in the share of firms with positive R&D spending both across industries and across regions.

4 - Empirical strategy

4.1 Methodology

We model the decision to innovate as a dynamic discrete choice panel data model. The dynamic framework would be justified by the existence of sunk costs (Sutton 1991), the hypothesis of “success breeds success” (Mansfield 1968) and the hypothesis that innovations involve dynamic increasing returns (Nelson and Winter 1982).[15] Although the purpose of our paper is not to study the presence of persistence *per se* in the decision to innovate, it is interesting to note that the latter hypothesis states that dynamic increasing returns in the form of learning-by-doing enhance the knowledge stocks and, therefore, the probability of future innovations. Since a firm’s absorptive capacity is likewise a function of the stock of knowledge, learning in one period will allow for a more efficient accumulation of external knowledge in subsequent periods (Cohen and Levinthal 1989). Hence, the cumulative nature of knowledge should also induce state dependence in innovation behaviour. Therefore, in order to test for the relevance of a firm’s absorptive capacity in the decision to innovate, one has to account for the state dependence, so that the estimated coefficient does not reflect such persistence.

The econometric specification is written as:

$$y_{it} = 1(\alpha_1 y_{it-1} + \delta' x_{it} + \eta_i + u_{it} > 0) \qquad (1)$$

where t=1,…,T and i=1,…,N. Also, **1**(…) is the usual indicator function and it is assumed that the time-variant error term $u_{it}/\ y_{i0}, y_{i1},\dots, y_{it-1}, x_i$ ~iid N(0,1) and that $u_{it} \perp \eta_i$ where $x_i = (x_{i1},\dots, x_{iT})$.

[15] See Máñez-Castillejo *et al.* (2004) and Peters (2005), and the references cited therein, for a thorough revision of all this literature.

Equation (1) models the decision of firm i to innovate as a function of its past innovative behaviour (y_{it-1}), some observable determinants (x_{it}), unobserved firm-specific heterogeneity (η_i) and other time-variant unobserved components uncorrelated with x_{it}.[16]

For estimation purposes we will have to tackle three important theoretical and practical problems: First, the treatment of the unobserved heterogeneity η_i, secondly, the handling of the initial condition y_{i0}, and thirdly, the possibility that some of the regressors in x_{it} are not strictly exogenous. As regards the first two problems, we follow Wooldridge (2005) in our estimation strategy. Therefore, we employ a correlated random effects framework à la Chamberlain (1980) whereby we model the distribution of the unobserved effect conditional on the initial value and any explanatory variables in order to partial it out from the likelihood function. A priori, a fixed effects estimator would seem to be preferable, since it does not make any assumptions about the distribution of η_i. However, we are interested in the magnitudes of the partial effects, which depend not only on the covariates x_{it} but also on the distribution of the unobserved heterogeneity –more on this below. The correlated random effects framework allows us to avoid the uneasy RE assumption of independence between x_{it} and η_i, but at the same time allowing for some correlation. Further, following Wooldridge (2005), you can conveniently specify a distribution of η_i that suits you well from a computational perspective.

Concerning the second problem, you have to decide how to treat the initial condition, since the joint density of (y_{i1},…, y_{iT}) given (y_{i0}, x_i, η_i) is

$$\prod_{t=1}^{T} f_t(\mathrm{y}_{\mathrm{t}} / y_{t-1}, x_t, \eta; \theta) \tag{2}$$

which depends on y_{i0} when t=1. Wooldridge (2005) suggests to model the distribution of η_i conditional on y_{i0} and x_i, which allows to integrate out η_i and leads to the joint density of (y_{i1},…, y_{iT}) given (y_{i0}, x_i). Then, MLE conditional on (y_{i0}, x_i) can be used, which can be computationally simple. In order to follow this strategy, we assume that the firm-specific heterogeneity depends on the initial condition and the strictly exogenous variables in the following way:

$$\eta_i = \beta_0 + \beta_1 y_{i0} + \beta_2 x_{i0} + a_i \tag{3}$$

where it is further assumed that a_i ~iid $N(0,\sigma^2_a)$ and that $a_i \perp (y_{i0}, x_{i0})$, and thus:

$$\eta_i \approx N(\beta_0 + \beta_1 y_{i0} + \beta_2 x_{i0}, \sigma^2{}_a) \tag{4}$$

Hence, the probability of being an innovator is given by:

$$P(y_{it} = 1 / y_{i0},..., y_{it-1}, x_i, x_{i0}, a_i) = \Phi(\alpha_1 y_{it-1} + \delta' x_{it} + \beta_0 + \beta_1 y_{i0} + \beta_2 x_{i0} + a_i) \tag{5}$$

[16] We will relax this assumption below. The list of potential endogenous variables contains human capital variables, such as the share of skilled workers, financial variables (equity share, debt-assets ratio, share of banking debt) or market concentration variables. In our short sample (2003-2007), market conditions are unlikely to change much in response to firms' innovative activities, so endogeneity would not be an issue with regards to market structure variables.

which yields a likelihood function that has the same structure as in the standard RE panel data probit model.
It has to be noted, though, that Wooldridge (2005) suggested using either the time averages[17] of x_{it} or the whole vector $x_i=(x_{i1},\ldots, x_{iT})$ in order to model the distribution of the individual heterogeneity, as put forward by Chamberlain (1980). However, given that this estimator requires a balanced panel, which limits the number of observations, and that we are potentially dealing with some endogenous covariates, we opted to include the initial value of the explanatory variables x_{i0} instead. This way, we reduce the number of explanatory variables and, at the same time, avoid estimation biases, since if some variables in x_{it} are not strictly exogenous, then some of the elements in $\sum_t x_{it}$ or in x_i would be correlated with the error term u_{it}. Moreover, much of the information contained in either $\sum_t x_{it}$ or in x_i is embedded in x_{i0} since there exists a relatively high degree of persistence in most of these variables.

As regards the third problem, endogeneity is tackled in two ways: playing with the lags between the decision to innovate and the outcomes of that decision, and using control function methods à la Rivers-Vuong and Blundell-Smith, as in Papke and Wooldridge (2008). Firstly, and in line with most of the empirical literature on innovation, we will estimate our empirical specifications including all covariates lagged one period. The rationale for this is the following: at the beginning of time t, when managers gather to decide whether to undertake innovative activities or not, their information set contains the explanatory variables up to t-1. Some of these variables are exogenous to their decision to innovate, such as the sector capital intensity or the stock of public knowledge available in a particular region, while others are not. The latter –indeed, most of the variables in our study– can be regarded as predetermined, since they reflect choices made in the past and are not affected by future decisions about innovation. For instance, the growth rate of real sales would reflect the innovative effort made in the recent past in order to improve the quality of a firm’s products, but, a priori, there are no particular reasons to expect that current sales reflect the expected decision to innovate in, say, three years time.

However, there are some regressors that may be potentially endogenous to the decision to innovate. Some of them have already been identified, such as financial variables (equity share, debt-assets ratio, share of banking debt) or market concentration variables, while others have received less attention in the literature on innovation, such as the share of skilled-labour or of temporary workers. As regards market structure variables, in our short sample (2003-2007), market conditions are unlikely to change much in response to firms’ innovative activities, so endogeneity would not be an issue. Moreover, since the focus of this paper is not on financial issues, we will not pay a particular attention to the endogeneity of the financial ratios. Hence, we will try to deal carefully with the simultaneity of human capital variables.

There are several reasons to expect the share of qualified personnel to be related to technological factors. Indeed, according to the theories that emphasize the role of skill-biased technological change, the share of skilled-labour would be determined by the technological content of the productive process and, hence, endogenous to the decision to innovate. Additionally, this share in period t would reflect innovative choices made in periods t,t-1,t-2,… but, also, it would be reasonable to expect it to depend on technological choices expected in t+1,t+2,…,t+k. Similar arguments can be made for the portion of fixed-term employees or for training expenditures.

[17] That is $\bar{x}_i = T^{-1}\sum_{t=1}^{T} x_{it}$

As a consequence, we will deal with endogeneity as in Papke and Wooldridge (2008), who present an attractive framework to estimate nonlinear panel data models where endogeneity might be an issue in the spirit of Rivers and Vuong (1988). In order to do this, let us express our structural model as:

$$E(y_{it} / w_{it}, z_i, \eta_i, u_{it}) = E(y_{it} / w_{it}, z_{1it}, \eta_i, u_{it}) = \Phi(\alpha_1 y_{it-1} + \delta' z_{1it} + \gamma' w_{it} + \eta_i + u_{it}) \tag{6}$$

where the vector w_{it} contains the potentially endogenous variables, that can be correlated with u_{it}, and the exogenous variables are $z_{it}=(z_{1it}, z_{2it})$, where we need some time-varying, strictly exogenous variables z_{2it} to be excluded from (6). We also model the unobserved heterogeneity as in (3):

$$\eta_i = \beta_0 + \beta_1 y_{i0} + \beta_2 z_{1i0} + a_i \tag{7}$$

where $a_i/z_i \sim N(0,\sigma^2_a)$. Equation (7) can be plugged into (6) to arrive to a similar expression as (5). Next, we have to assume a linear reduced form for the endogenous variables, w_{it}:[18]

$$w_{it} = \psi_0 + \psi_1 y_{i0} + \psi_2 z_{i0} + \psi_3 z_{it} + v_{it} \tag{8}$$

where, if necessary, we can allow the coefficients in (8) to depend on t. The addition of y_{i0} and z_{i0} follows from the Chamberlain (1980)'s correlated RE device, as in equation (3). The nature of endogeneity of w_{it} is through the correlation between u_{it} and v_{it}, the reduced form error. If it is further assumed that $u_{it} = \lambda v_{it} + e_{it}$, where $e_{it}/(z_i, v_{it}) \sim N(0,\sigma^2_e)$, then it can be shown that the structural model has the following form:

$$E(y_{it} / w_{it}, z_i, v_{it}) = \Phi(\alpha_{e1} y_{it-1} + \delta_e' z_{1it} + \gamma_e' w_{it} + \beta_{0e} + \beta_{1e} y_{i0} + \beta_{2e} z_{1i0} + \lambda_e v_{it}) \tag{9}$$

where the subscript "e" denotes division by $(1+\sigma^2_e)^{1/2}$. This equation is the basis for estimation. Papke and Wooldridge (2008) propose a simple two-step estimation procedure for the scaled coefficients which consists of 1) estimating the reduced form for w_{it} and obtaining the residuals $\hat{v}_{it}$ for all (i,t) pairs, and 2) estimating the probit of y_{it} on y_{it-1}, w_{it}, z_{1it}, y_{i0}, z_{1i0}, $\hat{v}_{it}$ to estimate the scaled coefficients. They also suggest using two-step pooled methods, because they are very computationally attractive. To be more specific, we will use a pooled probit for the first stage and a pooled probit QMLE for the second stage. Moreover, due to the two-step nature of the procedure, the standard errors in the second stage have to be adjusted for the first stage estimation. We will use bootstrap methods in our empirical exercise. Further, it has to be noted that a test of endogeneity of w_{it} is easily obtained as an asymptotic t statistic on $\hat{v}_{it}$.

4.2 Variables

[18] In this exposition, we assume, for simplicity, that we have a single endogenous explanatory variable.

4.2.1 Dependent variable

We will define an innovative company as a firm that exhibits positive R&D expenditures in a given year.[19] This choice is determined by the fact that this is the only available proxy for innovation we have at our disposal in the Central de Balances database. It implies that we analyze the role of absorptive capacity variables from the point of view of innovation inputs, which might be different than that for the behaviour of innovation outputs. Given the tight link found in the literature between inputs and outputs in the innovation process (see Crépon *et al.* 1998), we believe that this distinction is not so relevant. This notwithstanding, as we are aware that this choice may be somehow problematic, we will use two additional proxies for innovative activities –more on this below– which result from matching our database with the PITEC database. The first alternative dependent variable is an indicator variable that takes the value of one when a firm has positive innovation expenditures in the corresponding year –which are a broader measure that encompasses R&D outlays–. The second one, which is more outcome-oriented, is a dummy variable that equals one whenever a company declares to be involved in an innovative project that has not been finalized yet or has been abandoned as of date t.

As it can be seen in Table 6, which shows transition probabilities for our main dependent variables, the innovation behaviour is highly persistent at the firm level, both in the larger (unbalanced) sample and in the constrained (balanced) sample. In both samples about 89% of innovating firms in one period continued to be innovative in the subsequent period, while 11% ceased to be innovators. Similarly, around 97% of non-innovative firms maintained this status in the following period, while just 3% of them became innovative firms. In other words, the likelihood of being innovative in period t+1 was nearly 87 percentage points higher for innovators than for non-innovators. Finally, the transition probabilities for (positive) innovation expenditures are quite similar than those for R&D expenditures.

4.2.2 Spillovers and the absorptive capacity of a firm

As we have emphasized in the second section, the literature on R&D has stressed the role of knowledge spillovers in the decision to invest (Griliches 1992). Spillovers may be understood as knowledge borrowed by research teams in one firm from the ideas generated by other firms in either the same industry or in a different sector, even across regions or countries. In this vein, and with the purpose of analyzing the relevance of different types of spillovers, we have built several measures of spillovers using aggregate data at both the sector and regional level. We have computed the stock of business R&D capital –using the perpetual inventory method– for each of the different industries at the national level and for each region irrespective of the industry,[20] so that we can study whether it is more relevant the stock of knowledge capital at a regional level or at an industry level. Moreover, we have also calculated the stock of public R&D capital by region[21] –there was no sector disaggregation for this variable–. Further, another way to take into account these spillovers is that suggested by Máñez-Castillejo *et al.* (2004). Region-specific spillovers are captured by the fraction of firms that perform R&D activities in the same region, irrespectively of the corresponding two-digit industry. Industry-specific spillovers are the fraction of firms that perform R&D activities in the same industry, be they in the same region or not.

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[19] See Table 5 for a description of all the variables used in the estimation exercise.
[20] See Table 5 for a description and Table 7 for some summary statistics.
[21] This includes R&D spending of both high education institutions and public administration.

However, we have argued in Section 2 that, in order to take advantage of these spillovers, firms have to develop their own research skills. Thus, in line with some of the literature, such as Griffith *et al.* (2003, 2004), Jaffe (1986) or Guellec and Van Pottelsberghe (2004), we proxy a firm's absorptive capacity in our baseline specification with its R&D intensity, measured as R&D spending over total sales.[22] However, following the seminal paper of Cohen and Levinthal (1989) we have also tried a specification where the absorptive capacity depends on the firm's R&D capital stock, rather than the flow. Additionally, we will also study the role of some human capital variables in the decision to innovate, both their direct impact and indirect one, which we will link to absorptive capacity. More concretely, we consider the skill composition of a firm's labour force and provision of on-the-job training (measured as the share of managers, professionals and technicians in total employment and real training expenditures per employee, respectively), and some measures of job instability –the share of temporary employees–.

4.2.3 Other controls

The empirical literature traditionally distinguishes several groups of variables that determine the decision to innovate, besides those related to the existence of spillovers and firms' absorptive capacity. The incentive to invest in R&D depends on the economic and technological opportunities faced by the firm, on appropriability conditions, on market characteristics, on the business cycle and other macroeconomic factors and, finally, on other unclassified determinants. As regards the economic opportunities (Schmookler 1962), these are determined by factors such as the expected future demand, the size and growth of the market and the willingness of society to pay for new or improved products. To proxy for these things we consider the growth rate of firms' sales, in order to account for firm- and sector-specific demand shocks,[23] and time dummies, to capture macro-level changes, such as the business cycle.

Another group of variables influencing the decision to innovate relates to technological opportunities. The usual way to proxy for this, which we follow, is to employ two-digit industry dummies. Also, it has been argued that technological opportunities decrease with the life cycle of the firm's product (Cohen, Levin and Mowery 1987), since newly born firms are typically very innovative (Huergo and Jaumandreu 2002). There should be, then, an inverse relationship between age and the propensity to innovate at the industry level. In order to control for this, we include the variable age measured as the difference between the current year and the year of foundation reported by the firm.

Appropriability conditions are also a main determinant of the decision to undertake innovative activities. The literature has found two opposing effects of low levels of appropriability on R&D investment. On the one hand, there is the traditional disincentive effect because of the difficulties to appropriate the benefits of a firm's own investments (Schumpeter 1942, Arrow 1962). On the other hand, when appropriability is low, spillovers

[22] There might be some objections to the use of lagged R&D intensity as a regressor, since the dependent variable is also a function of R&D expenditures. Note, however, that we already take into account the role of state dependence, i.e., we include the lagged dependent variable and the initial condition in the regressions. Thus, the impact of R&D intensity goes beyond capturing state dependence, and we link that impact to firms' absorptive capacity.

[23] We also included the growth rate of industry sales, but it turned out to be non significant, so it was removed.

among firms are higher and, in order to profit from them, firms may need to invest in R&D with the purpose of developing sufficient absorptive capacity (Cohen and Levinthal 1989). To control for appropiability conditions we introduce the total number of patents granted in the same region where the firm operates, which is a variable that is calculated using data for the whole economy disaggregated by region from the National Statistics Institute.[24]

Market characteristics, such as the degree of market concentration and competition, have an important role in the decision to innovate. The degree of market power has traditionally been highlighted as a crucial determinant of innovation (Schumpeter, Arrow), since it allows firms to prevent imitation and, thus, appropriate returns from innovation. Moreover, increased monopolistic power means higher price-to-cost margins, which enhances the financing of innovative activities via higher profits. Additionally, as far back as Scherer (1967) it was established the potential existence of an inverted U-shaped relationship between competition and innovation. On the one hand, innovation should decline with competition, as more competition reduces the monopoly rents that reward successful innovators. On the other hand, firms have to innovate in order to stay in business owing to competitive pressures, particularly in industries with a higher degree of neck-and-neckness (see Aghion *et al*. 2002). Therefore, the incentives to innovate increase with moderate amounts of competition, where the escape-competition effect predominates, and then fall due to the excess competition and the Schumpeterian effect of reduced appropriability of profits. In order to account for this, several indicators of market power were computed: two measures of concentration, the concentration ratio of the three largest firms in the relevant market and the market share of the 10% largest firms, a proxy for the price-to-cost margin[25] and the Herfindahl index –which is computed for the employment share using data from the DIRCE, which is a database that registers basic information about the population of all firms–, and finally, the (in-sample) market share of each firm. Although Artés (2008) shows the importance for innovation of using several indicators of competition in his study of the Spanish manufacturing sector, we will see that none of these variables turned out to be significant in our regressions. Another important issue regarding market power is the threat posed by potential competition from entrants. Barriers to entry can both weaken or favour the incentives for innovation. The Schumpeterian view expects a positive effect from barriers to entry, while others argue that they reduce the stimulus to introduce new products. Barriers to entry can be proxied by the average capital intensity of the industry (Kraft 1989). In our case, we calculate the (in-sample) industry average of plant and equipment assets per worker.

It is a commonly held view that innovation activities are difficult to finance in a competitive market setting with capital from sources external to the firm. In other words, there exists a gap between the rate of return required by the entrepreneur investing his own funds and that required by external investors (Arrow, 1962). Therefore, unless the innovative firm is already profitable, some innovations will fail to materialize only because of too high a cost of external capital. Hall (2002) provides an excellent review of both the theoretical and empirical literature on internal finance and R&D, so we are not going to survey these questions in depth. She highlights some features of this type of investment[26] that imply that

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[24] We would have liked to build an industry-level measure, such as the one used by Beneito (2003), which is the ratio between the total number of patents granted and the total number of firms that assert to have achieved innovations in the firm's industrial sector. However, we cannot build the same proxy, since we do not have the number of patents granted to the firms in our database.

[25] Computed as (gross operating surplus – financial expenditures)/sales.

[26] First of all, R&D investment –the main innovative activity– has a high degree of uncertainty associated with its output, which tends to be greatest at the beginning of the research project. Research programs usually have small probabilities of great success in the future, so that the asymmetric information problem is enhanced. Investors have more difficulty distinguishing good projects from bad and, thus, charge a higher risk premium for

debt or equity finance will be relatively more expensive for R&D than for ordinary investment, which suggests an important role for retained earnings –cash flow– in the decision to innovate, as has been shown by the pioneer works of Hall (1992) and Himmelberg and Petersen (1994).

Hence, we are going to introduce some measures of financial constraints in our empirical exercise. The first is the ratio of equity to liabilities, as a measure of the relevance of cash flows and retained earnings on the decision to innovate. The second is the share of short-term liabilities to total liabilities, as a measure of financial vulnerability, since these liabilities must be refinanced each year out of current cash flows and R&D projects usually lack a regular stream of cash flows. And the third one is the share of bank loans on total liabilities. This latter variable is crucial in the Spanish case, since it has a bank-dominated financial system.

Indeed, a number of recent papers have stressed the role played by bank finance in fostering or hampering innovation. The development of financial intermediaries may help reduce the cost of acquiring information and allow a better assessment, selection and monitoring of R&D projects. Another channel that is particularly relevant in the Spanish economy is through bank competition and the expansion in the supply of credit that it brings. The period under study, 2003-2007, has witnessed a substantial increase in bank credit in a context of lax financial conditions which has flowed to most sectors of activity, although particularly so to the housing sector, which may have crowded-out credit flows to other sectors, for instance, the research sector. However, other authors argue that relationship-based bank financing discourages new technologies because bank officers are unable to evaluate them. Overall, the empirical literature tends to find a positive effect of bank financing on innovation, although there are some exceptions.[27]

Finally, a number of firm characteristics has also been stressed by the literature as important determinants of the propensity to innovate. Firm's size:[28] innovations are so expensive that only large firms can support them, due to the existence of fixed (sunk) costs or economies of scale that allow to spread the cost of R&D between more units of output (this is what Cohen and Klepper call "cost spreading" and applies not only to firm's size but to the size of the market as well). In addition, large firms can undertake more innovation projects of the same magnitude than small firms so that they can pool the risks and reduce aggregate risk (Kraft 1989). Firm size is measured by the (log) number of employees, as in most of the literature.

Further, the degree of international competition is measured by the penetration of imports in the industry where the firm operates, while the degree of internationalization is proxied by a dummy variable that takes the value of one when the firm reports positive export earnings. Indeed, firms operating in international markets are exposed to different competitive settings which, among other things, could be the source of new ideas leading

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financing. Moreover, the information asymmetry cannot be reduced through greater transparency, because firms are reluctant to reveal their innovative ideas for fear of being imitated. Second, the knowledge asset created by R&D investment is intangible, partly embedded in human capital and usually very firm-specific, whereas creditors prefer to use tangible assets as collateral for their loans. Third, R&D programs are characterized by an uncertain and unstable stream of cash flows, which undermines debt financing, since servicing this debt requires a stable source of cash flows.

[27] Benfratello *et al.* (2008), Herrera and Minetti (2007) and Huynh and Rotondi (2007), using similar data for the Italian economy, find evidence in favour of a positive effect of bank financing, in particular, for innovative activities of firms in high-tech sectors, that depend more on external finance and that have a lengthy credit relationship. Additionally, some of the results suggest that relationship-based lending has a benefit on innovation not by fostering R&D, but by channelling funds for the introduction of new technologies. On the contrary, Atanassov *et al.* (2007), using a large panel of US companies, find that firms relying more on arms' length financing (equity and debt) have a larger number of patents.

[28] For a thorough study on the relationship of size and R&D see Cohen and Klepper (1996).

to innovation (see Cassiman and Martínez-Ros 2005 for the Spanish case). Moreover, some authors have stressed that foreign owned firms are less likely to engage in innovative activities. One potential reason is the fact that R&D activities play a crucial role in the long term strategy of a company and managers wish to keep direct control over such activities, thus R&D activities are usually located close to the companies' headquarters (Bishop and Wiseman 1999). We control for this factor with a dummy variable that equals one when a foreign company has a positive share in a firm's equity. Additionally, we account for the fact that the company may receive funding from the public sector in the form of subsidies to fixed capital. This is justified by the fact that, to the extent that fixed capital and knowledge capital are complementary inputs in the productive process, then subsidizing physical assets could have a positive impact on the accumulation of knowledge capital.

Table 7 reports the descriptive statistics for the variables used in the estimation exercise. It turned out that for almost all variables the variation across firms (between variation) is higher than the variation within firms over time. Further, 25% of the observations correspond to innovative firms.

5 - Econometric results

5.1 Main results

Table 8 reports the estimation results for the dynamic RE probit model using a balanced panel for the period 2003-2007. In addition, we compare our results with the static pooled and RE models, as well as with a dynamic RE model which only controls for the initial condition. Moreover, the static models are estimated for the whole sample (1991-2007) in order to check whether the results are very sensitive to the estimation period –which they are not, see below.

The first result that is worth remarking is the fact that the lagged dependent variable is a relevant determinant of the decision to innovate. Even after accounting for individual unobserved heterogeneity, past innovative experience is highly significant, thus confirming the existence of true state dependence. The results further show that the initial condition is also highly significant, which, in our estimation framework, implies that there is a substantial correlation between firms' "pre-sample" innovation status and firm-specific heterogeneity. Moreover, the statistical significance of several variables tends to weaken, or even disappear, when we go from the static to the dynamic specifications –see export status, share of skilled labour, the equity ratio and the share of banking liabilities–. There are two interpretations to this result. The first one would point to the fact that some of these variables, which are themselves highly persistent, might be picking up the impact of the lagged dependent variable in the static regressions. The second explanation is related to the way we model the unobserved heterogeneity. Given the short time span considered in the estimation exercise and the somewhat high persistence of some of these variables, including the covariates in t=0 might be detracting statistical significance from those variables.

It is also worth remarking that the results provide evidence that firm-specific heterogeneity is a key factor for innovation persistence. The importance of this variable in explaining the variance of the likelihood of innovation can be gauged from the statistic ρ, which measures the share of the variance of the dependent variable explained by unobserved heterogeneity.[29] In the static models, that share amounts to over 80% of the variation in the dependent variable, while in the dynamic models there is a marked reduction to between 12% and 18%. Moreover, it has to be highlighted that the Wald test on the joint significance of the explanatory variables in t=0, which were included to account for the correlated RE framework, fails to reject that they are not statistically significant (see the Wald-Heterogeneity line under the final column). Additionally, the LR test on the null hypothesis that ρ=0 also failed to be rejected, which is somehow counterintuitive. The results of these two tests are features that hold for all the estimates that we are going to present; therefore we opted to consider the specification where we model firm-specific heterogeneity as:

$$\eta_i = \beta_0 + \beta_1 y_{i0} + a_i \qquad (10)$$

as our baseline specification (fifth column in Table 8), in contrast to equation (3).[30] The results are quite similar in this case than when we model η_i as in (3), except for a slight decrease in the statistical significant of some variables. These estimates are available upon request.

However, the most important finding is that in addition to past innovation experience, the existence of spillovers coming from the stock of "sector" knowledge generated by other firms and the firm's capacity to assimilate that knowledge, as measured by the R&D intensity, are a crucial determinant of the decision to innovate. The stock of knowledge generated in the same sector of activity of a firm (k priv-sec) has a positive impact on its probability to innovate; however, this effect is enhanced when we account for the firm's absorptive capacity, proxied by the ratio of R&D expenditure over sales (k priv-sec*R&D intensity). Indeed, if we compute the average partial effect[31] for these two variables (more on this below, in section 5.2), then we have a coefficient of 0.023 for the stock of knowledge capital and of 0.113 for its interaction with the R&D intensity. In other words, the marginal impact of knowledge spillovers on the probability of innovation would increase six-fold, from 0.023 to 0.136, for a firm that raises its R&D-to-sales ratio from 0% to 1%, which is substantial.

Moreover, the direct impact on the probability of innovation of human capital variables, such as the share of skilled workers and the share of temporary workers, is also significant. That is, firms with a higher share of skilled workers have a larger probability of doing R&D activities, while those which have a greater portion of temporary workers tend to have a lower propensity to innovate. On the other hand, the coefficient for training expenditures is less precisely estimated, although overall tends to be positive, and statistically significant for the whole sample in static models. All in all, these results highlight the important role of spillovers, the absorptive capacity and human capital variables in the dynamics of firms' innovation behaviour.

[29] In other words, $\rho=\sigma_a^2/(1+\sigma_a^2)$.

[30] An additional advantage is that we conserve on degrees of freedom as we avoid overparameterization.

[31] Notice that in order to compute the average partial effect one has to multiply the scale factor (see the "scale factor for APE" at the bottom of the table) by the estimated coefficient. This also allows comparing the results from the different methods of estimation, which are not directly comparable due to different normalizations.

There are some additional firm characteristics that are found as well to be relevant in explaining the innovation decision. As regards financial factors, firms that have a larger share of short term liabilities are less likely to invest in R&D, since they are more likely to be financially constrained. Moreover, the presence of bank financing seems to be beneficial for innovation, thus confirming the hypothesis that commercial banking ameliorates the monitoring problem of capital markets. In other words, financial intermediaries help reduce the cost of acquiring information and allows a better assessment, selection and monitoring of R&D projects. Finally, firms with a higher share of equity, i.e. with more internal resources, are more likely to engage in R&D activities, as expected.

Furthermore, the proxy for appropriability conditions –the number of patents per region– has a negative and statistically significant coefficient, which suggests that the larger the appropriability, the lower the incentives to innovate, since firms cannot easily profit from spillovers. Besides, firms that received public funding for capital expenditures (capital grants) in the previous period exhibit a higher propensity to innovate in the subsequent period than firms without such financial support. Likewise, we find that exporting firms tend to have a higher probability of being innovative, as expected. Shocks to firms' demand, as proxied by the growth rate of sales, and firm size have a positive impact on innovation, as found in previous papers.

However, and contrary to most literature, we do not find any significant impact of market structure variables on the decision to innovate. This result would be consistent with the idea that, in general, changes in the market structure of an industry take time to materialize and, since we are working with a five-year sample, it is difficult to capture their effect on firms' decisions. This might also be due to the fact that we have used bad proxies to account for market structure factors. Yet, besides using the firm's market share, the degree of import penetration and the measure of concentration based on the market share of the 10% largest firms, we have checked for the robustness of our results including the price-to-cost mark-up and two other measures of concentration, one based on the market share of the 3 largest firms and another one based on the Herfindahl index. This last variable has been built using data on employment from the DIRCE, which is closer to the "desired" population. These variables turned out to be non significant either and did not alter the main thrust of our results.

Another sensitivity analysis that we implement is to compare our baseline results with those coming from estimating our model for the whole sample, in order to check the stability of our results, both across time and across firms, since we are working with a sub-sample. Since the dynamic methods require balanced panels, we only estimate static pooled and RE probits (see columns 2 and 4 in Table 8).[32] Now, we have 2,500 firms and 16,590 observations. Overall, there are not many significant differences in the estimation results, which underpins the robustness of our empirical exercise. We would highlight, however, that, in the whole sample training expenditures turn out to be a statistically significant driver of innovation –as we already mentioned above–, while the degree of import penetration negatively affects the decision to invest in R&D.

Given our focus on human capital variables as catalysts of innovative activities within firms, we present in Table 9 the results of an exercise that accounts for the role of those

[32] We have to do away with the stock of private sector knowledge capital and its interaction with R&D intensity because we cannot compute these variables for the whole sample due to lack of data.

variables as enhancers of firms' absorptive capacity. In other words, we try to disentangle whether the impact of human capital variables comes from their ability to improve firms' absorptive capacity or from other factors. In order to do this, we replace the interaction between "k priv-sec" and "R&D intensity" with the interaction between "k priv-sec" and a human capital variable, one at a time.[33] In the second column it can be seen that, on the one hand, skilled workers tend to improve firms' capability to absorb spillovers and, thus, encourage innovation, but on the other, skilled labour *per se* tends to diminish the probability of innovation. This last result, though counterintuitive at first, could be rationalized as in Kraft (1989). He argues that this kind of workers is mostly employed to fulfil administrative tasks (e.g. accounting, marketing, finance, etc). Hence, a high percentage of skilled-workers can indicate that a firm has a bureaucratic structure, which impedes innovative activity. In fact this is what he finds in his empirical exercise. [34]In short, we provide some evidence that the positive sign attached to this variable in the baseline equations may be due to the fact that it is accounting for an enhanced absorptive capacity rather than better qualifications of the workforce.

The amount of resources devoted to training is also positively and statistically significantly related to the decision to innovate through its impact on the firm's absorptive capacity, while the direct impact would be positive but non-significant. On the contrary, the share of fixed-term employment does not seem to hamper the absorption of external spillovers and, thus, innovative activities, since the coefficient is negative, but statistically insignificant. Its impact on these activities would come from other channels, such as less motivation or less acquisition of specific human capital, as suggested by Albert *et al.* (2004) for the Spanish case. The rest of the results are, overall, quite similar qualitatively, although quantitatively the coefficients are less precisely estimated.

5.2 Magnitude of the effects and policy implications

In this section we provide some estimates of the increase in the probability of undertaking innovative activities that can be expected from the main variables in our study. In order to do this, we firstly compute the partial effects of these variables. Given that they depend on firm-specific heterogeneity, we can compute the partial effects at the average (PEA), which are the partial effects for the average individual in the sample. However, this has the drawback that usually the average value is not representative of a large share of the firms. Therefore, it is preferable to estimate the average partial effect (APE), which is the average of all individual partial effects across time in the sample.[35]

Table 10 contains the results of these estimates for our baseline regression (fifth column, Table 8). The first column shows the average value of the variables taken into consideration, while in the second column we provide the assumed change in the concerned variable, which will be, for simplicity, 10%, and in the third column we include the APE for our baseline specification. The final column calculates the estimated change in the probability of innovation for each variable. The first effect that we consider is the direct effect of undertaking innovative activities on the subsequent probability of being an

[33] We run a regression including the interaction of "k priv-sec" with all human capital variables at once and the results were similar. This is available upon request.
[34] Additionally, Romijn and Albalejo (2002) find that the share of technicians in a firm's labour force decreases its probability of innovation while the percentage of engineers increases it. He argues that this result reflects the fact that only specialized knowledge and experience in science and engineering, rather than practical intermediate-level skills, are important for innovation. In our exercise we are not able to distinguish between engineers and technicians, which could explain the lack of robustness of the coefficient of skilled labor.
[35] See Annex A and Wooldridge (2002, 2005) for a deeper analysis of these issues.

innovator. This can be regarded as a sort of intertemporal effect that arises as a consequence of the strong state dependence of this type of activities. The partial effects, thus, provide the change in innovative status between t and t+1, from non-innovator to innovator. In other words, it computes $P(y_{it}=1/\ \mathbf{y_{it-1}=1},x_i,\eta_i)-P(y_{it}=1/\ \mathbf{y_{it-1}=0},x_i,\eta_i)$ averaged out across firms and time. As we can see in the table, controlling for differences in observed and unobserved characteristics, the propensity to innovate in period t is approximately 47 percentage points higher for innovators than for non-innovators in period t-1. This contrasts with the transition probabilities calculated in Section 4.1, which showed that the change in the propensity to innovate between the two types of firms was close to 87 percentage points.[36]

Moreover, we also compute the "double face" effect of R&D investment, which is an indirect effect related to its role as enhancer of absorptive capacity. In this case, for an assumed 10% increase in R&D intensity, we estimate that the probability of reporting positive R&D investment would increase by about 1 percentage point, which represents around 4% of the actual frequency of conducting R&D (25% is the sample mean), which is a non-negligible figure. As regards the human capital variables, we may see that the one with the greatest impact is the share of temporary employment, with a partial effect of -0.069. The share of skilled workers also has a relatively high impact, while training expenditures have a small one. The partial effects of financial variables are quite similar across them and, for a 10% change, they imply variations in the propensity to innovate in the order of between 0.2 and 0.3 percentage points, a similar impact than that from the stock of sector knowledge capital.

In sum, it is clear that the main factor affecting the propensity to innovate is the presence of true state dependence. Nevertheless, the impact from the double role of R&D investment is also significant, and that from other factors, such as human capital variables or financial variables, is smaller, though non-negligible.

5.3 Endogeneity

In this section we empirically analyze the potential endogeneity of human capital variables. Firstly, in order to do this, we have to find some instrumental variables that must satisfy two conditions: i) they must be uncorrelated with the unobservable time-varying error term u_{it}, and ii) they must be sufficiently correlated with the endogenous variables that we want to instrument.[37] This is a difficult task in our particular context, since most variables at the firm level that can be correlated with the human resource management variables might be deemed to be, at the same time, jointly determined with the decision to innovate. Hence, given the difficulty of exploiting firm-level variation in order to identify the parameters of interest, we have searched for instruments outside our sample, trying to exploit the regional variation[38] of some interesting variables.

The first such variable –see Table 5 for definitions and sources– is the share of immigrants in total population by province, which is a determinant of the potential labour supply of temporary workers, since they are more prone to work in any type of job. At the same time, since it has been documented that they have a lower educational level, this share would

[36] Peters (2005), using a similar methodology, estimates a difference of between 23 and 36 percentage points for German manufacturing firms and of between 8 and 13 for services firms.

[37] There is another requirement, the order condition, which ensures that there is at least one instrumental variable for each endogenous regressor in order to identify the parameter of interest.

[38] Spanish regions (Comunidades Autónomas) are divided into provinces. We use both regional and provincial variation.

be negatively correlated with the availability of skilled labour. Moreover, given their lower education and their different cultural background one would expect these people to be somehow more eligible to receive on-the-job training, so that this variable would be positively correlated with training expenditures. Additionally, we have used the unemployment rate by province as an instrument. The larger the unemployment rate, the more willing a person is to accept a fixed-term contract. At the same time, one could argue that a higher unemployment rate could result in a depreciation of human capital, as long term unemployment begins to rise and this, in turn, results in a deterioration of the skills of the unemployed. Hence, this would affect negatively the supply of skilled labour. Another relevant determinant of this supply is the share of people with higher education, by province. Besides, these people are less prone to end up with a temporary employment and one would expect them to be more likely to receive on-the-job training.

Further, we have built a dummy variable that equals one when a firm has signed a firm-level collective bargaining agreement. One would expect that in firms with this type of agreement –where the influence of trade unions on management practices is arguably higher– the prevalence of fixed-term contracts is lower than in the other firms, since trade unions tend to oppose them. Also, it is likely that trade unions in these firms tend to favour on-the-job training programs, so a positive correlation between this dummy and the training expenditures would be expected. Finally, we have used as an instrument the share of women, between 15 and 64 years old, in the population of the province. To the extent that women tend to be better qualified, as measured by the number of years of formal education, they increase the potential supply of skilled-labour.[39]

As described in section 4.1, in the first stage we have regressed the human capital variables on all exogenous regressors and on all instrumental variables using a pooled probit with a fully robust variance matrix. Then we have tested whether the latter variables are jointly statistically significant. Indeed, in the case of skilled labour, the robust Wald test gives a p-value of 0.001, although individually only the coefficients for the share of women and the unemployment rate are significant.[40] As regards fixed-term employees, the Wald test gives a zero p-value to three decimal places. In this case, the share of immigrants, the unemployment rate and the firm-level collective agreement dummy are statistically significant. And finally, the equation for training expenditures obtains the worst results, with a Wald test with a p-value of 0.109 and the unemployment rate as the only significant IV. Overall, the strength of these variables as instruments might be deemed as not quite satisfactory, which provides an avenue for future work.

In the second stage we have estimated equation (9) adding as a covariate the vector of estimated residuals from the first stage, using a pooled probit QMLE. Table 11 contains the results for this second stage. The first column reports the baseline regression estimated with a dynamic RE probit model, while the second column reports estimates using the pooled probit QMLE, in order to check the comparability of both estimation methods. In short, the estimated coefficients are quite similar and we detect that those from the QMLE are a bit lower. The last column shows the estimates when human capital variables are allowed to be endogenous. First of all, the Wald test on the joint significance of $\hat{v}_{it}$ fails to reject, with a zero p-value to the three decimal places, which provides evidence against the null hypothesis that human resource management variables are

[39] We have also tried other interesting instrumental variables, such as the share of young people by province, the sector volatility of real sales or per-student public expenditure on education by region, but they were not significantly correlated with human capital variables.
[40] Results are available upon request.

exogenous. If we look at the individual coefficients for these residuals, the failure of exogeneity would seem to come from training expenditures, the only residual statistically significant.

As regards the rest of estimated parameters, they are quite similar, both quantitative[41] and qualitatively, although there are some remarkable differences. The coefficient on the skilled labour variable is lower in the endogenous case, and it also loses its statistical significance, while on the other hand, that for training expenditures increases fivefold and becomes significant. The parameter on temporary employment roughly doubles and retains its significance. Overall, these results show that care should be taken in using human resource management variables in order to explain firms' innovation behavior, since they are likely to be endogenous.

5.4 Further Robustness Analysis

Some further sensitivity analyses are carried out in this section in order to check the robustness of our results and explore some additional issues. Firstly, we have built an expanded balanced panel which extended from 2000 to 2007, but with only over 500 firms. We have estimated our baseline specification again for the period 2003-2007 but, in this case, in order to account for unobserved heterogeneity using a correlated RE framework, we have used the time average of the covariates for the period 2000-2002, instead of just the covariates in 2002. This exercise barely affected the results; hence, they are not reported here, but are available upon request.

Secondly, we have run the baseline regression and regressions in Tables 12 and 13 replacing our preferred measure of spillovers –R&D intensity– with the stock of R&D. The results are quite similar and are available upon request. Thirdly, we run the baseline regression substituting our reference measure of spillovers, so that we can check whether we could detect other relevant spillovers besides those coming from firms in the same sector of activity. In order to do this, we built two other stocks of knowledge capital using aggregate national statistics from INE, the National Office of Statistics: one stock of knowledge capital from public sector institutions[42] in the same region of the firm (k pub-ca) –and no matter the sector– and other stock of private knowledge capital of all firms in the same region (k priv-ca), irrespective of their sector of activity. Table 12 shows that these two types of technology capital seem to generate relevant knowledge spillovers, both alone and when interacted with the absorptive capacity variable. An additional implication is that not only industry spillovers matter –the traditional focus in most of the literature–, but those coming from the public research sector and from firms in other industries (in the same region) matter as well.[43]

In line with Máñez-Castillejo *et al.* (2004), we have also computed the share of innovative firms in the same sector of activity across the whole country, as well as in the same region where the firm is located, irrespective of the industry, in order to account for industry-specific spillovers and region-specific spillovers. Most of the literature emphasizes the role of spillovers within the industry, given the technological proximity, but a number of papers suggest that geographical proximity generates positive externalities, market linkages and

[41] Note that quantitative comparisons are facilitated by the fact that the scale factor is similar.
[42] We capitalize R&D expenditures from public sector institutions and from the higher education sector, in line with previous literature (see Guellec and Van Pottelsberghe 2004). This makes sense since the public sector controls the budget –and even the research agenda– of higher education institutions in most countries.
[43] When all measures of knowledge capital are included together, then only industry spillovers are significant and the interaction with R&D intensity becomes non-significant.

possibilities for cooperation that, in turn, encourage innovation activities. Again, what we find (Table 12, columns 4 and 5) is that technological spillovers, both at the industry or regional level, only matter as long as you have previous experience in R&D, or in other words, absorptive capacity.

Overall, these results would be consistent with Jaffe (1986), Harhoff (2000) and Beneito (2001), who found positive significant effects of spillovers to the extent that this variable was combined with the own level of knowledge capital, which can be interpreted as a measure of a firm's absorptive capacity.

Finally, we have checked the sensitivity of our results to different measures of the dependent variable since, as it is well known, R&D expenditures may not be a good proxy for innovation. In order to do this we have merged our database with the PITEC database, which results in a balanced panel of around 460 firms for the period 2003-2007. PITEC is an interesting database because we can use total innovation expenditures instead of only R&D expenditures to generate the dependent variable,[44] which, obviously, is a better proxy for the decision to innovate. Besides, and contrary to other variables in similar databases, we have the data year by year, without overlapping, which would introduce artificial persistence. As can be seen in Table 13 (second column) the results are reasonably similar and, in particular, the interaction between spillovers and absorptive capacity remains highly significant. The rest of covariates lose a bit of significance, probably due to the fact that we are working with a smaller sample in both time and individuals dimensions. We have also used another interesting dependent variable from PITEC, Innofin, which is a dummy variable that equals one whenever a firm is currently involved in an innovative project that has not been finished yet or has just abandoned a research project. Again, this information is available on a yearly basis which avoids overlapping. Table 13 (third column) shows that the main thrust of our results remains unaltered: the interaction between the stock of private industry knowledge capital and the firms' R&D intensity, the share of skilled-labour and the portion of temporary workers are statistically significant with the expected signs.

6 - Conclusions

We have studied the role played by knowledge spillovers and firms' absorptive capacity, as well as by the quality of human capital, in the decision to innovate using data on Spanish firms for the period 2003-2007. In order to do this, we have used the estimator proposed by Wooldridge (2005) for dynamic binary choice panel data models. The empirical exercise has provided some evidence on the positive effect of spillovers on firms' innovative behaviour, an effect which is enhanced for those firms with a higher capacity to absorb those spillovers. The results also confirm and highlight the role of some human resource management practices on the dynamics of firms' inventive performance.

The basic result from the analysis of spillover effects is that they are relevant not just for the knowledge generated in the same industry, but also for that generated in the same region and in different industries throughout the country. Moreover, it has been shown that the capacity to assimilate those spillovers is not only a function of firms' R&D capabilities – as traditionally envisaged–, but of such factors as the quality of the labour force, the share

[44] R&D expenditures account for around 43% of total innovation expenditures, and both variables have a correlation coefficient of 0.49 in this particular subsample.

of temporary employment and the amount of resources spent in training, as well. Indeed, our results suggest that the effects of skilled labour and of on-the-job training work mainly through its impact on firm's absorptive capacity. In addition to these factors, we have found that innovation performance exhibits true state dependence and that unobserved heterogeneity plays an important role in explaining the persistence of innovation. Further, some other observed firm characteristics, such as size, sales growth, export behaviour, sector capital intensity or financial variables (like the equity share, the percentage of short-term liabilities or the portion of banking loans), are also found to be relevant determinants of the likelihood of innovation.

From an economic policy point of view, the distinction between permanent innovation activities due to firm-specific factors as opposed to true state dependence has important implications for innovation policy, as argued by Peters (2005). If innovation performance shows true state dependence, policies such as government support programmes are supposed to have a more profound effect, because they not only affect the current innovation activities but are likely to induce a permanent change in favour of innovation. If, on the contrary, individual heterogeneity induces persistent behaviour, support programmes are unlikely to have long–lasting effects and economic policy should concentrate more on measures which have the potential to improve innovation–relevant firm–specific factors.

Further, and in particular for the Spanish economy, our results would provide an additional argument in favour of tackling the high prevalence of temporary employment, since it seems to be detrimental for firms' innovation performance. Moreover, given the fact that Spanish firms are not only lagging behind R&D spending, but also in the skill qualification of its workforce and in on-the-job training, it will not be enough to devote large quantities of public resources to support R&D activities; policy-makers have as well to make sure that Spanish corporations are able to benefit from that effort.

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Tables

Table 1: Central de Balances coverage rates

Database coverage[1], 2005

	Value-added	*Employment*	*Wages*
Energy	71.3	57.5	79.1
Industry	28.5	18.1	27.4
Mkt. Services	20.4	23.7	26.3
Other [2]	7.6	6.7	10.2

1 Ratio CB firms' to National Accounts' non-financial sector aggregate
[2] Includes agriculture and construction

Table 2: Sample description (I)

Period average	Sample		
	Extended	*Restricted*	*CB-PITEC*
Number of firms	2565	787	470
Number of observations	23082	4722	1340
Minimum nº of consecutive obs. per firm	4	6	5
Median nº of consecutive obs. per firm	8	6	5
Balanced?	no	yes	yes
% innovating	24.9	25.2	35.8
Sector distribution			
energy & utilities	4.3	6.1	5.1
industry	38.9	36.2	46.9
market services	38.5	39.7	31.9
other[1]	18.3	18	16.1
Size distribution			
SMEs[2]	53.6	47.7	27.5
Large	46.4	52.3	72.6
% exporting	57.8	58.6	71.1
% stock market	7	7.1	9.7

[1]Includes extraction, agriculture, fishing and construction
[2]250 or less employees

Table 3: Sample description (II)

	Extended			Restricted			CB-PITEC		
sector	Observations	% of total	% R&D>0	Observations	% of total	% R&D>0	Observations	% of total	% R&D>0
Agriculture and forestry	288	1.25	19.44	33	0.70	27.27	1	0.04	100.00
Fishing	4	0.02	0.00	0	0.00	0.00	0	0.00	0.00
Extraction of fuels	165	0.71	37.58	30	0.64	36.67	10	0.43	50.00
Extraction of other minerals	46	0.20	21.74	0	0.00	0.00	0	0.00	0.00
Manufacture of food products, beverages and tobacco	1793	7.77	25.21	311	6.59	26.69	174	7.40	35.06
Manufacture of coke and refined petroleum products	142	0.62	72.54	36	0.76	80.56	20	0.85	65.00
Manufacture of chemicals and chemical products	1759	7.62	59.86	341	7.22	62.46	222	9.45	68.47
Manufacture of other minerals	795	3.44	30.82	127	2.69	27.56	96	4.09	25.00
Manufacture of basic metals	1147	4.97	37.05	268	5.68	37.69	185	7.87	39.46
Manufacture of machinery and equipment	821	3.56	57.25	138	2.92	70.29	83	3.53	83.13
Manufacture of electrical equipment	875	3.79	59.77	135	2.86	57.78	90	3.83	64.44
Manufacture of transport equipment	1052	4.56	43.16	210	4.45	48.57	140	5.96	58.57
Manufacture of textiles	747	3.24	20.62	122	2.58	29.51	85	3.62	34.12
Manufacture of articles of fur, leather and footwear	129	0.56	20.16	36	0.76	22.22	20	0.85	30.00
Manufacture of wood and of products of wood and cork	214	0.93	23.83	36	0.76	50.00	25	1.06	60.00
Manufacture of paper and paper products	698	3.02	15.62	176	3.73	19.32	85	3.62	20.00
Manufacture of rubber	383	1.66	33.68	66	1.40	31.82	45	1.91	37.78
Other manufactures	361	1.56	27.70	54	1.14	16.67	25	1.06	28.00
Energy, gas and water	533	2.31	45.40	162	3.43	37.65	65	2.77	69.23
Water collection, treatment and supply	461	2.00	10.20	128	2.71	10.94	55	2.34	16.36
Construction	1624	7.04	12.13	275	5.82	9.82	90	3.83	21.11
Trade	3813	16.52	7.76	850	18.00	10.94	374	15.91	16.04
Transport and communications	1780	7.71	9.44	437	9.25	10.53	175	7.45	19.43
Hotels and restaurants	646	2.80	1.08	168	3.56	0.00	60	2.55	0.00
Real state and other professional services	2806	12.16	13.15	583	12.35	11.49	225	9.57	20.00
Total	23082	100	24.90	4722	100	25.20	2350	100	35.80

Table 4: Sample description (III)

	Extended			Restricted			Restricted		
	Observations	% of total	% with R&D>0	Observations	% of total	% with R&D>0	Observations	% of total	% with R&D>0
Andalucia	1444	6.26	12.26	216	4.57	8.80	70	2.98	14.29
Aragon	639	2.77	26.13	144	3.05	35.42	90	3.83	45.56
Asturias	535	2.32	19.07	108	2.29	10.19	55	2.34	16.36
Baleares	387	1.68	6.72	92	1.95	2.17	20	0.85	0.00
canarias	560	2.43	6.43	102	2.16	0.98	15	0.64	0.00
Cantabria	274	1.19	26.64	66	1.40	27.27	30	1.28	50.00
Castilla la mancha	329	1.43	19.15	84	1.78	23.81	35	1.49	48.57
Castillas y León	679	2.94	33.28	182	3.85	35.71	78	3.32	48.72
Cataluña	5674	24.58	29.56	1330	28.17	26.02	697	29.66	35.87
Com. Valenciana	1905	8.25	20.68	306	6.48	25.49	135	5.74	34.07
Extremadura	34	0.15	64.71	6	0.13	100.00	5	0.21	100.00
Galicia	826	3.58	15.98	138	2.92	18.12	55	2.34	29.09
La Rioja	67	0.29	19.40	14	0.30	0.00	7	0.30	0.00
Com. De madrid	7193	31.16	25.34	1358	28.76	26.36	723	30.77	34.44
Murcia	401	1.74	9.98	102	2.16	13.73	55	2.34	21.82
Navarra	442	1.91	31.00	98	2.08	34.69	62	2.64	46.77
País Vasco	1656	7.17	38.65	364	7.71	39.56	218	9.28	47.71
Ceuta y melilla	37	0.16	0.00	12	0.25	0.00	0	0.00	0.00
Total	23082	100	24.9	4722	100	25.2	2350	100	35.8

Table 5

VARIABLE DEFINITION	
Variable	***Definition***
Alternative endogenous variables	
Innovation	=1 if a firm i has positive R&D expenditures in year t. These expenditure include those outlays incurred to discover new knowledge and to develop that knowledge into a design for a new product or a new productive process.
Inno_exp	=1 if a firm i has positive innovation expenditures in year t. These include R&D spending, acquisiton of external knowledge, machines and equipment, training, market introduction, design and other preparations for product and/or process innovations. Data from PITEC
Innofin	=1 if firm i has an innovative project that has been abandoned or has not been finalized yet as of date t. Data from PITEC
Explanatory variables	
Size	Number of employees of firm i in year t-1, in logs
Age	Age of firm i in year t-1 compue as the difference between the current year and the year of foundation, in logs
Sales growth	Growth rate of real sales of firm i in year t-1, deflated with a value-added deflator
Sectoral K-intensity	Per-industry average of fixed-physical assets per worker in year t-1, deflated with value-added deflator, in logs
Foreign ownership	=1 if a foreing firm has a share in firm i's equity in year t-1
Export	=1 if firm i reports positive sales in foreing markets in year t-1
Subsidies to K	=1 if firm i reports receiving positive subsidies to fixed-physical assets from either the Spanish public sector or the EU in year t-1
Patents-ca	Number of patents in the same region than firm i in year t-1, computed with data from INE for the whole economy
Kpriv-sec	Aggregate stock of knowledge capital for the private business sector at a sectoral level in year t-1, in logs, computed with data from INE for the whole economy
Kpub-ca	Aggregate stock of knowledge capital for the public sector at a regional level in year t-1, in logs, computed with data from INE for the whole economy
Kpriv-ca	Aggregate stock of knowledge capital for the private business sector at a regional level in year t-1, in logs, computed with data from INE for the whole economy
Kpriv-sec*R&D intensity	Product of (log) Kpriv-sec and the ratio of R&D expenditures over sales of firm i, lagged one year; the same holds for Kpub-ca and Kpriv-ca
%Innovfirm-sec	Percentage of innovative firms (R&D>0) in the same industry than firm i in year t-1
%Innovfirm-ca	Percentage of innovative firms (R&D>0) in the same region than firm i in year t-1
%Skilled-labour	Percentage of managers, professionals and technicians in total employment in firm i in year t-1
%Fixed-term labour	Percentage of employees on a temporary contract in firm i in year t-1
Training spending	Real training expenditures per employee in firm i in year t-1, deflated with value-added deflator
Equity/Liabilities	Ratio of equity to the sum of equity and liabilities of firm i in year t-1
%Short-term liabilities	Ratio of short-term liabilities to total liabilities for firm i in year t-1
%Banking liabilities	Ratio of bank loans to total liabilities for firm i in year t-1
Concentration	Market share of the first decile of firms with larger sales by year and industry, lagged one year
Market share	Market share of firm i's sales in year t-1
Import penetration	Share of imports in total sales by industry in year t-1
Instrumental variables	
%Women	Share of women aged 15-64 in total population, by province. Source: INE (National Statistics Office), "Padrón Municipal" (municipal census)
Unemployment rate	Unemployment rate by province. Source: INE, Labour Force Survey (EPA)
%Higher educ.	Share of people with terciary and upper-level vocational training education by region. Source: INE, Labour Force Survey (EPA)
%Immigrants	Share of immigrants on total population, by region. Source: INE, Municipal Census
Firm-level coll. barg.	Dummy variable that equals 1 if a firm has a firm-level collective agreement. Source: Statistics on Collective Agreements, Minsitry of Labour and Immigration

Table 6

Transition probabilities

	Innovation status in t+1: Balanced panel (2002-2007)			Unbalanced panel (1991-2007)		
Innovation status in t:	Innovation = 0	Innovation = 1	Total	Innovation = 0	Innovation = 1	Total
Innovation = 0	97.1	2.9	100	95.8	4.2	100
Innovation = 1	10.5	89.5	100	10.9	89.1	100
Total	74.9	25.1	100	74.3	25.7	100

Transition probabilities for innovation expenditures (PITEC)

	Innovation status in t+1: Balanced panel (2003-2007)		
Innovation status in t:	Innovation = 0	Innovation = 1	Total
Innovation = 0	86.2	13.8	100
Innovation = 1	6.2	93.8	100
Total	34	66	100

Table 7

Descriptive statistics for relevant variables

Variable	Unit	Estimation sample (2003-2007) Mean	Std. Dev. Overall	Std. Dev. Between	Std. Dev. Within	Min	Max
Innovation	1/0	0.251	0.434	0.398	0.173	0	1
Size	logs	5.84	1.44	1.43	0.160	2.20	9.31
Age	years	35.58	28.03	28.01	1.41	1	217
Sales growth	y-o-y %ch.	3.34	23.57	9.93	21.37	-262.53	297.22
Sectoral K-intensity	logs	4.58	1.65	1.59	0.45	-0.59	9.06
Foreign ownership	1/0	0.202	0.402	0.386	0.114	0	1
Export	1/0	0.588	0.492	0.477	0.124	0	1
Subsidies to K	1/0	0.272	0.445	0.352	0.273	0	1
Patents-ca	nº pat.	440.87	256.42	254.31	35.73	0	752
Kpriv-sec	logs	13.56	1.58	1.55	0.307	10.00	16.67
Kpub-ca	logs	14.41	1.09	1.08	0.159	7.25	15.57
Kpriv-ca	logs	14.64	1.47	1.46	0.173	4.14	15.90
Kpriv-sec*R&D intensit	logs	0.060	0.198	0.186	0.068	0	1.47
Kpriv-sec*%Skilled-L	logs	3.22	3.27	3.18	0.770	0.003	15.61
Kpriv-sec*%Temp-L	logs	2.34	2.91	2.82	0.726	0	16.01
Kpriv-sec*Training-exp	logs	1.86	4.24	3.65	2.14	0	68.00
%Innovfirm-sec	%	25.11	19.60	19.07	4.60	0	83.33
%Innovfirm-ca	%	25.11	9.47	9.11	2.61	0	100
%Skilled-labour	%	23.28	22.35	21.74	5.25	0.02	93.65
%Fixed-term labour	%	17.19	20.85	20.13	5.48	0	96.01
Training spending	logs	0.135	0.308	0.264	0.159	0	5.70
Equity/Liabilities	%	67.51	26.32	24.34	10.06	6.87	100
%Short-term liabilities	%	56.85	35.97	31.87	17.44	0	100
%Banking liabilities	%	59.65	42.11	38.35	17.85	0	100
Concentration	%	61.45	12.22	11.79	36.47	34.05	83.75
Market share	%	1.77	3.54	3.46	0.76	0.01	18.60
Import penetration	%	22.71	23.25	22.61	5.46	0	74.71

Table 8

Baseline regression: comparing static pooled, static RE and dynamic RE probit models

	Pooled	Pooled (1991-2007)	Static RE	Static RE (1991-2007)	Dynamic RE only y(i,0)	Dynamic RE y(i,0) and x(i,0)
Innovation(t-1)	---	---	---	---	2.197***	2.261***
					0.187	0.211
Innovation(t=0)	---	---	---	---	0.996***	0.887***
					0.311	0.350
Size	0.211***	0.281***	0.533***	0.648***	0.133**	0.334
	0.048	0.029	0.108	0.049	0.054	0.237
Age	-0.053	0.003	0.010	0.060	-0.050	0.311
	0.059	0.032	0.124	0.057	0.048	0.348
Sales growth	0.269*	0.169***	0.317	0.134	0.410**	0.430**
	0.151	0.048	0.253	0.084	0.199	0.205
Sectoral K-intensity	-0.034	-0.021	-0.043	0.044	-0.071*	0.084
	0.045	0.022	0.080	0.034	0.044	0.084
Foreign ownership	-0.148	-0.133**	-0.301	-0.119	-0.008	-0.258
	0.125	0.065	0.217	0.091	0.118	0.238
Export (yes/no)	0.669***	0.554***	1.001***	0.754***	0.252*	0.119
	0.136	0.071	0.255	0.091	0.137	0.269
Subsidies to K (yes/no)	0.263***	0.293***	0.185	0.156**	0.172*	0.182
	0.090	0.051	0.142	0.063	0.105	0.120
Patents per region	-0.0004**	---	-0.0007*	---	-0.0005**	-0.002*
	0.0002		0.0004		0.0002	0.001
Kpriv-sec	0.209**	---	0.324*	---	0.271**	0.104
	0.104		0.182		0.128	0.160
Kpriv-sec * R&D intensity	8.891***	---	8.168***	---	1.309***	1.128**
	1.568		0.767		0.401	0.502
%Skilled-labour	0.842***	1.020***	1.654***	1.030***	0.475*	-0.113
	0.273	0.141	0.517	0.204	0.270	0.574
%Fixed-term labour	-0.640**	-0.397***	-1.149**	-0.893***	-0.804**	-1.211**
	0.325	0.133	0.590	0.185	0.346	0.610
Training spending	-0.089***	0.143*	-0.081	0.180***	0.051	0.046
	0.032	0.087	0.053	0.055	0.037	0.047
Equity/Liabilities	0.182	0.280***	0.801**	0.483***	0.372*	0.656*
	0.192	0.095	0.361	0.128	0.205	0.347
%Short term liabilities	-0.168	-0.141**	-0.445**	-0.091	-0.326**	-0.458**
	0.124	0.069	0.226	0.080	0.142	0.196
%Banking liabilities	0.360***	0.174***	0.592***	0.269***	0.223*	0.403**
	0.116	0.064	0.209	0.075	0.127	0.184
Concentration	-2.466	-2.952	-0.305	-3.761	5.238	8.010
	5.048	2.073	10.221	2.882	9.301	9.423
Concentration^2	2.408	2.670	1.688	3.940	-3.111	-6.062
	4.253	1.802	8.509	2.529	7.711	7.815
Market share	2.901*	-1.211	2.272	-2.641	1.554	-3.495
	1.697	1.212	3.486	1.655	1.802	4.341
Import penetration	-0.289	-0.742**	-0.987	-1.357***	-0.484	-0.328
	0.591	0.295	1.096	0.443	0.904	0.992
σ_η	---	---	2.118	2.303	0.464	0.367
			0.159	0.078	0.185	0.241
ρ	---	---	0.818	0.841	0.177	0.119
			0.022	0.009	0.116	0.137
LR_ρ (p-value)	---	---	0.000	0.000	0.070	0.202
Scale factor for APE	0.181	0.244	0.091	0.105	0.086	0.084
Wald-heterogeneity (p-value)	---	---	---	---	---	0.640
Firms	742	2511	769	2512	769	740
Observations	3550	16590	3682	16592	3682	3603

***, ** and * denote statistical significance at a 1%, 5% and 10% level, respectively. Standard errors in pooled probit adjusted for clustering on firms.

Time and industry dummies are included in each regression, but not reported. LR_ρ is a Likelihood-ratio test for $\rho=0$.

The scale factor allows to obtain the APE of each variable by multiplying this factor by the estimated coefficient.

Wald-heterogeneity is a Wald test on the joint significance of x(i,0), the explanatory variables in t=0.

Table 9

Impact of human capital variables on absorptive capacity

Dynamic RE probit model		Absorptive capacity variables:		
	Baseline (R&D invest.)	Skilled-labour	Temporary employment	Training expenditures
Innovation(t-1)	2.197***	2.351***	2.370***	2.353***
	0.187	0.176	0.176	0.178
Innovation(t=0)	0.996***	1.106***	1.059***	1.031***
	0.311	0.332	0.328	0.327
Size	0.133**	0.135**	0.141***	0.141***
	0.054	0.055	0.055	0.054
Age	-0.050	-0.051	-0.045	-0.046
	0.048	0.059	0.058	0.057
Sales growth	0.410**	0.415**	0.401**	0.388*
	0.199	0.199	0.198	0.199
Sectoral K-intensity	-0.071*	-0.085*	-0.083*	-0.074*
	0.044	0.045	0.044	0.044
Foreign ownership	-0.008	0.004	0.003	-0.002
	0.118	0.119	0.118	0.116
Export (yes/no)	0.252*	0.234*	0.236*	0.221*
	0.137	0.139	0.138	0.136
Subsidies to K (yes/no)	0.172*	0.150	0.162	0.174*
	0.105	0.107	0.105	0.105
Patents per region	-0.0005**	-0.0005**	-0.0005**	-0.0005**
	0.0002	0.0002	0.0002	0.0002
Kpriv-sec	0.271**	0.194	0.308**	0.276**
	0.128	0.135	0.136	0.129
Kpriv-sec * Aborptive cap.	1.309***	0.291**	-0.132	0.031***
	0.401	0.144	0.178	0.010
%Skilled-labour	0.475*	-3.521*	0.551**	0.451*
	0.270	2.023	0.267	0.267
%Fixed-term labour	-0.804**	-0.879**	0.922	-0.814**
	0.346	0.357	2.441	0.347
Training spending	0.051	0.070*	0.067*	0.052
	0.037	0.037	0.037	0.037
Equity/Liabilities	0.372*	0.361*	0.378*	0.357*
	0.205	0.207	0.205	0.202
%Short term liabilities	-0.326**	-0.349**	-0.353**	-0.311**
	0.142	0.144	0.142	0.141
%Banking liabilities	0.223*	0.221*	0.218*	0.226*
	0.127	0.128	0.127	0.126
Concentration	5.238	5.383	6.796	5.757
	9.301	9.438	9.371	9.431
Concentration^2	-3.111	-3.274	-4.335	-3.396
	7.711	7.289	7.766	7.839
Market share	1.554	1.262	0.845	0.770
	1.802	1.849	1.818	1.793
Import penetration	-0.484	-0.436	-0.475	-0.539
	0.904	0.909	0.908	0.903
σ_η	0.464	0.501	0.482	0.454
	0.185	0.186	0.188	0.194
ρ	0.177	0.200	0.188	0.171
	0.116	0.119	0.119	0.121
LR_ρ (p-value)	0.070	0.053	0.064	0.086
Scale factor for APE	0.086	0.087	0.087	0.087
Firms	769	769	769	769
Observations	3682	3682	3682	3682

***, ** and * denote statistical significance at a 1%, 5% and 10% level, respectively.

Time and industry dummies are included in each regression, but not reported. LR_ρ is a Likelihood-ratio test for ρ=0.

The scale factor allows to obtain the APE of each variable by multiplying this factor by the estimated coefficient.

Table 10

Magnitude of the effects of some relevant variables

Variables	Sample avg.	Assumed change	APE	Effect on P(y=1)
R&D investment:				
- Direct effect (innova(t-1))	0.251	P(1/1)-P(1/0)	0.473	47.3
- Indirect effect (spillover*abs. capacity)	0.060	10%	0.113	1.13
Spillovers:				
- Sectoral stock of R&D capital		10%	0.023	0.23
Human capital variables:				
- %Fixed-term labour	0.172	-10%	-0.069	0.69
- %Skilled-labour	0.233	10%	0.041	0.41
- Training expenditures	0.135	10%	0.004	0.04
Financial variables:				
- Equity ratio	0.675	10%	0.032	0.32
- %Short-term liabilities	0.569	-10%	-0.028	0.28
- %Bank financing	0.597	10%	0.019	0.19

Note: Computed using our preferred specification.

Table 11

Estimates allowing human capital variables to be endogenous

Baseline regression	Exogenous regressors		Instrumental variables
	Dynamic RE probit model	Pooled QMLE probit model	Pooled QMLE probit model
Innovation(t-1)	2.197***	2.398***	2.512***
	0.187	0.121	0.139
Innovation(t=0)	0.996***	0.601***	0.625***
	0.311	0.127	0.147
Size	0.133**	0.108***	0.158***
	0.054	0.038	0.057
Age	-0.050	-0.048	-0.059
	0.048	0.051	0.059
Sales growth	0.410**	0.405**	0.369*
	0.199	0.173	0.216
Sectoral K-intensity	-0.071*	-0.070*	-0.089**
	0.044	0.038	0.045
Foreign ownership	-0.008	-0.0003	-0.030
	0.118	0.104	0.125
Export (yes/no)	0.252*	0.236**	0.260**
	0.137	0.112	0.127
Subsidies to K	0.172*	0.169*	0.167
	0.105	0.093	0.107
Patents per region	-0.0005**	-0.0004**	-0.0005***
	0.0002	0.0002	0.0002
Kpriv-sec	0.271**	0.244*	0.234
	0.128	0.133	0.147
Kpriv-sec * R&D intensity	1.309***	1.147***	1.018**
	0.401	0.319	0.403
%Skilled-labour	0.475*	0.414*	0.266
	0.270	0.215	0.685
Residual skilled-labour			0.271
			0.732
%Fixed-term labour	-0.804**	-0.674**	-1.509**
	0.346	0.274	0.757
Residual fixed-term labour			0.967
			0.762
Training spending	0.051	0.043	0.217***
	0.037	0.029	0.046
Residual training spending			-0.247***
			0.045
Equity/Liabilities	0.372*	0.312*	0.334*
	0.205	0.166	0.193
%Short term liabilities	-0.326**	-0.286**	-0.280**
	0.142	0.119	0.140
%Banking liabilities	0.223*	0.189*	0.201
	0.127	0.110	0.139
Concentration	5.238	4.684	5.962
	9.301	7.372	8.910
Concentration^2	-3.111	-2.875	-4.118
	7.711	5.842	7.000
Market share	1.554	1.402	-0.008
	1.802	1.390	1.979
Import penetration	-0.484	-0.435	-0.399
	0.904	0.881	0.963
Wald exogeneity (p-value)			0.000
Scale factor for APE	0.086	0.086	0.084
Firms	769	769	767
Observations	3682	3682	3674

***, ** and * denote statistical significance at a 1%, 5% and 10% level, respectively.
Time and industry dummies are included in each regression, but not reported.
The scale factor allows to obtain the APE of each variable by multiplying this factor by the estimated coefficient.
The instrumental variables are the share of women, the unemployment rate, the share of people with at least Secondary Education and the share of immigrants, all computed by province, and a dummy variable that equals one when a firm has a firm-level collective bargaining agreement. The standard errors for the pooled QMLE are robust and, for the instrumental variables case, are obtained by bootstrapping all the firms using 500 bootstrap replications. Wald exogeneity is a Wald test for the joint significance of the coefficients for the residuals in the second stage regression.

Table 12

Impact of different measures of aggregate spillovers

Dynamic RE probit model		Spillover variables:			
	Baseline (Kpriv-sec)	K pub-ca	K priv-ca	%innovating firms same sector	%innovating firms same CA
Innovation(t-1)	2.197***	2.178***	2.168***	2.277***	2.176***
	0.187	0.188	0.188	0.192	0.188
Innovation(t=0)	0.996***	0.984***	0.981***	0.979***	0.943***
	0.311	0.310	0.308	0.328	0.303
Size	0.133**	0.121**	0.110**	0.128**	.123**
	0.054	0.053	0.053	0.053	0.052
Age	-0.050	-0.049	-0.041	-0.051	-0.045
	0.048	0.057	0.057	0.057	0.056
Sales growth	0.410**	0.404**	0.401**	0.390**	0.392**
	0.199	0.198	0.199	0.197	0.196
Sectoral K-intensity	-0.071*	-0.073*	-0.073*	-0.070*	-0.066
	0.044	0.044	0.044	0.043	0.043
Foreign ownership	-0.008	0.004	0.004	0.027	0.010
	0.118	0.116	0.117	0.115	0.115
Export (yes/no)	0.252*	0.245*	0.227*	0.244*	0.216
	0.137	0.135	0.137	0.134	0.134
Subsidies to K	0.172*	0.181*	0.187*	0.172*	0.183*
	0.105	0.104	0.105	0.103	0.103
Patents per region	-0.0005**	-0.001***	-0.002***	-0.0005**	-0.0005**
	0.0002	0.0004	0.0005	0.0002	0.0002
Spillover variable	0.271**	0.140*	0.230***	-0.006	0.010
	0.128	0.085	0.087	0.009	0.006
Spillover var. * R&D intensity	1.309***	1.364***	1.342***	0.340***	0.741***
	0.401	0.401	0.394	0.123	0.218
%Skilled-labour	0.475*	0.433	0.411	0.511**	0.472*
	0.270	0.268	0.269	0.263	0.265
%Fixed-term labour	-0.804**	-0.789**	-0.737**	-0.869**	-0.753**
	0.346	0.340	0.341	0.342	0.339
Training spending	0.051	0.048	0.049	0.053	0.049
	0.037	0.036	0.036	0.036	0.036
Equity/Liabilities	0.372*	0.383*	0.362*	0.377*	0.363*
	0.205	0.203	0.203	0.201	0.201
%Short term liabilities	-0.326**	-0.323**	-0.323**	-0.321**	-0.301**
	0.142	0.141	0.142	0.140	0.139
%Banking liabilities	0.223*	0.238*	0.256**	0.213*	0.225*
	0.127	0.127	0.128	0.125	0.124
Concentration	5.238	5.245	5.502	5.116	5.874
	9.301	9.327	9.319	9.417	9.345
Concentration^2	-3.111	-3.889	-4.082	-3.898	-4.360
	7.711	7.741	7.727	7.781	7.760
Market share	1.554	1.340	1.278	1.341	1.552
	1.802	1.784	1.780	1.769	1.751
Import penetration	-0.484	-1.077	-1.046	-1.137	-1.039
	0.904	0.879	0.878	0.894	0.880
σ_η	0.464	0.447	0.446	0.438	0.424
	0.185	0.188	0.188	0.201	0.190
ρ	0.177	0.167	0.166	0.161	0.152
	0.116	0.117	0.117	0.124	0.116
LR_ρ (p-value)	0.070	0.083	0.083	0.103	0.098
Scale factor for APE	0.086	0.086	0.086	0.087	0.086
Firms	769	769	769	769	769
Observations	3682	3682	3682	3682	3682

***, ** and * denote statistical significance at a 1%, 5%and 10%level, respectively.

Time and industry dummies are included in each regression, but not reported. LR_ρ is a Likelihood-ratio test for ρ=0.

The scale factor allows to obtain the APE of each variable by multiplying this factor by the estimated coefficient.

Table 13

Different definitions of innovation

Dynamic RE probit model	Baseline (R&D invest.>0)	Alternative dependent variables: 1/ Innovation expenditures>0	Innofin (current or abandoned)
Innovation(t-1)	2.197***	1.337***	0.915***
	0.187	0.195	0.137
Innovation(t=0)	0.996***	1.630***	0.964***
	0.311	0.357	0.179
Size	0.133**	0.160*	0.081
	0.054	0.089	0.063
Age	-0.050	0.079	0.027
	0.048	0.098	0.068
Sales growth	0.410**	0.083	0.363
	0.199	0.332	0.263
Sectoral K-intensity	-0.071*	-0.072	0.016
	0.044	0.065	0.049
Foreign ownership	-0.008	-0.198	-0.074
	0.118	0.186	0.125
Export (yes/no)	0.252*	0.402**	0.366**
	0.137	0.196	0.148
Subsidies to K	0.172*	0.300*	0.269**
	0.105	0.159	0.109
Patents per region	-0.0005**	-0.0002	-0.000
	0.0002	0.0003	0.000
Kpriv-sec	0.271**	-0.042	0.104
	0.128	0.212	0.153
Kpriv-sec * R&D intensity	1.309***	5.645***	0.886***
	0.401	1.557	0.313
%Skilled-labour	0.475*	0.495	0.712**
	0.270	0.414	0.298
%Fixed-term labour	-0.804**	-0.669	-0.802**
	0.346	0.460	0.355
Training spending	0.051	0.008	0.042
	0.037	0.049	0.037
Equity/Liabilities	0.372*	0.094	-0.055
	0.205	0.301	0.224
%Short term liabilities	-0.326**	-0.358*	-0.190
	0.142	0.211	0.148
%Banking liabilities	0.223*	0.028	0.175
	0.127	0.185	0.132
Concentration	5.238	-31.040**	-10.257
	9.301	12.745	9.391
Concentration^2	-3.111	27.703***	9.404
	7.711	10.450	7.757
Market share	1.554	5.997	6.252***
	1.802	3.768	2.342
Import penetration	-0.484	0.950	0.309
	0.904	1.241	0.932
σ_η	0.464	0.859	0.660
	0.185	0.175	0.121
ρ	0.177	0.425	0.303
	0.116	0.100	0.078
LR_ρ(p-value)	0.070	0.000	0.000
Scale factor for APE	0.086	0.118	0.214
Firms	769	462	462
Observations	3682	1790	1790

***, ** and * denote statistical significance at a 1% 5%and 10%level, respectively.

Time and industry dummies are included in each regression, but not reported. LR_ρ is a Likelihood-ratio test for ρ=0.

The scale factor allows to obtain the APE of each variable by multiplying this factor by the estimated coefficient.

1/ Data for these regressions span 2004-2007

Annex 1: Computing partial effects

One problem in estimating partial effects is the fact that firm-specific heterogeneity is unobservable. In the case of a continuous covariate case, we would like to compute:

$$\frac{\partial P(y_{it}=1/y_{i0},...,y_{it-1},x_i,x_{i0},a_i)}{\partial x_{itj}} = \delta_j \phi(\alpha_1 y_{it-1} + \delta' x_{it} + \beta_0 + \beta_1 y_{i0} + \beta_2 x_{i0} + a_i) \quad \text{(A1)}$$

which clearly depends on the distribution of η_i (or, equivalently, a_i).

Hence, the literature has proposed two alternative calculation methods to deal with this shortcoming. The usual way to compute the partial effects is to calculate the so called partial effects at the average (PEA) by assuming that the individual heterogeneity takes its average value, which can be calculated, in our particular setting, as:

$$E(\mu_i) = \beta_0 + \beta_1 E(y_{i0}) + \beta_2 E(x_{i0}) \quad \text{(A2)}$$

Therefore, the estimated PEA, which would employ sample statistics for population analogs, would take the form:

$$PEA = \hat{\delta}_j \phi(\hat{\alpha}_1 \bar{y}_{-1} + \hat{\delta}' \bar{x} + \beta_0 + \beta_1 \bar{y}_0 + \beta_2 \bar{x}_0) \quad \text{(A3)}$$

The PEA, however, has the drawback that usually the average value is not representative of a large share of the firms. Alternatively, one can estimate the average partial effect (APE), which results from averaging the unobserved heterogeneity across firms. In other words, you can compute the partial effect for the average individual in your sample (the PEA) or the average of all individual partial effects across time in your sample (the APE). In analytical form, the estimated APE is:

$$APE = \hat{\delta}_{aj} \frac{1}{N} \frac{1}{T} \sum_{i=1}^{N} \sum_{t=1}^{T} \phi(\hat{\alpha}_{1a} y_{it-1} + \hat{\delta}_a' x_{it} + \beta_{0a} + \beta_{1a} y_{i0} + \beta_{2a} x_{i0}) \quad \text{(A4)}$$

where the subscript "a" denotes that the original parameters have been scaled by $(1+\sigma_a^2)^{-0.5}$.