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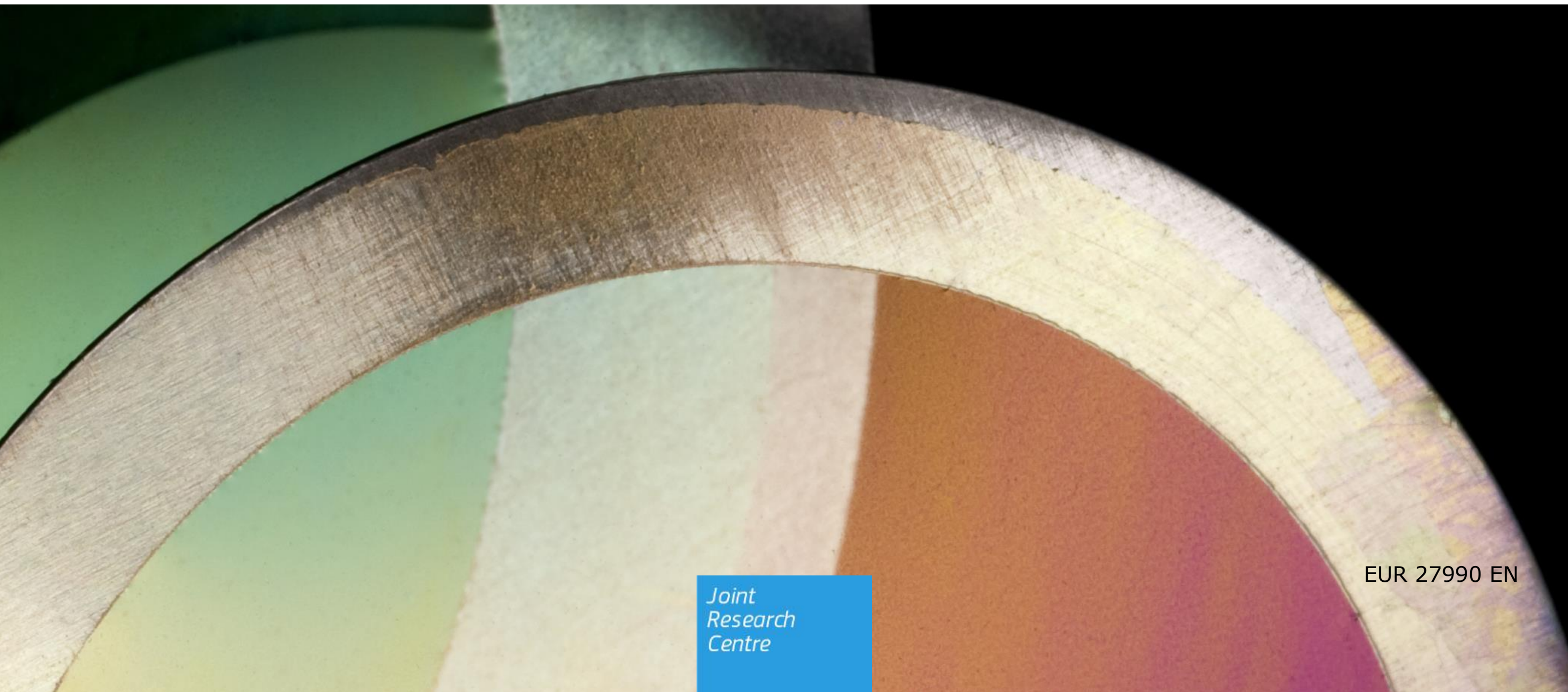

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Innovation and Productivity in an S&T-intensive Sector: Information Industries in Spain

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Abstract

This paper adds to the empirical literature on the relationships between R&D, innovation and productivity at the firm level. The focus is on Spanish enterprises in information industries, which are acknowledged to be at the forefront for both innovative activity and R&D performance. The analysis is performed on ca. 1,800 enterprises included in the PITEC database (the Spanish source for the EU Community Innovation Survey) for the period 2004-2013. Using a three-stage "CDM" model we consider: (i) factors affecting the decision to conduct R&D, including the role of the perceived importance of innovation on firm's R&D performance, (ii) the impact of the predicted R&D effort on companies' effective undertaking of product, process, organisational and marketing innovations, as well as their simultaneous occurrence and (iii) whether and to what extent these innovations boost productivity. In the specific context of this R&D-intensive array of industries, the decision to undertake R&D appears to be strongly influenced by the importance attributed to enhancing existing products or creating new ones, and also by the size of the company, whether they are young and/or local, and the availability public funding. These elements also greatly impact on enterprises' R&D efforts, thus providing some arguments in favour of R&D promotion policies, particularly if they address start-ups. Expected R&D performance, in turn, appears to be strongly related to the actual achievement of these innovations, including non-technical ones. By focusing on innovation patterns, it was possible to ascertain a strong complementarity between different families of innovation (as expected, given these industries' specificities), as well as to supplement existing evidence on the innovation-productivity conundrum. Indeed, we show that results depend on the way innovation types are modelled and combined. Controlling for complementarities, enterprises performing focused non-technical innovations and joint technical and non-technical ones (mixed-mode innovators) are likely to be more productive (in terms of sales per capita) than their peers, while stand-alone technical innovations give inconclusive results.

Keywords: R&D, innovation, ICT sector, productivity, firm level data, panel

JEL codes: O00, O31, O32, O47

1. R&D, innovation and productivity: the general landscape and Information Industries

R&D and innovation performance are tightly related, and acknowledged to impact on the capability of enterprises and countries alike to keep being competitive and grow. For advanced economies this is even more the case today, due to price competition stemming from cheaper labour in emerging competitors. R&D and innovation also have a positive – albeit complex – relationship to productivity.[1]

ICT industries rank high with respect to their R&D intensity, and their share of innovative enterprises and productivity levels. In the EU, the ICT sector contributes about 4% of GDP. This rises to nearly 6% when Content and Media activities (CM) are included in the broader *Information industries* aggregate that we address in this study due to data availability.[2] The share of these industries in EU Business Enterprise R&D (BERD) expenditure - 16.5% for the ICT industries alone, and about 21% if we consider the larger aggregate of information industries in the operational definition followed here - is much higher than their economic weight (see note 4). As a consequence, the R&D intensity of production (measured as the ratio between BERD and value added) can reach 20% and above in the case of ICT manufacturing and is about 5% in the ICT sector, against 1.1% in the rest of the economy. These industries are also far more productive than the average.

As shown in Figure 1, the value added share of ICT industries varies greatly across EU Member States, from 6% and above to about 2%, such differences depending mostly by the development of Information Technology (IT) services. In Spain, the share of ICT industries' value added is 3.7%, and almost 5% if we include CM.

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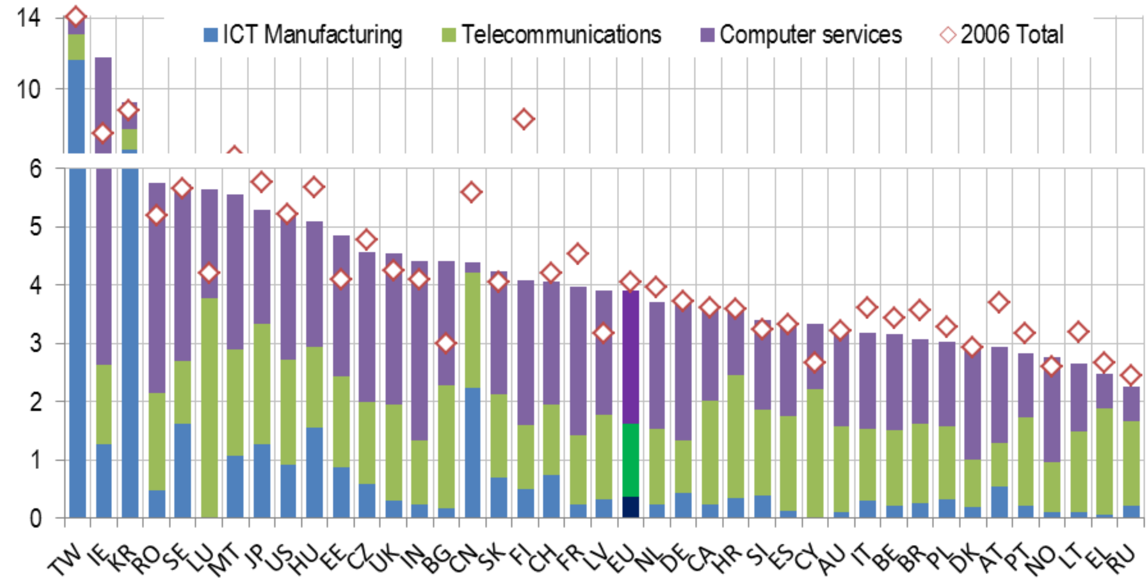
1 Seminal works in this field include the studies by Grossman and Helpman (1991), Scherer (1999), Hall and Mairesse (1995), which also report gains in productivity at the firm level.

2 Following the OECD (2007) definition, whereas ICT industries include manufacturing activities in ISIC rev.4 division 26 (excluding group 265 to 267), and service activities in group 582 (software publishing), divisions 61 (telecommunications), division 62 (computer programming) and group 631 (data processing), Information Industries also include CM activities, i.e. divisions 58 (all excluding group 582), 59 and 60, plus group 639, which together with ICT service activities form ISIC Section J, *Information and Communication Services*. Service activities should also include ICT wholesale trade (ISIC classes 4651 and 4652) and repair activities (group 951), which we do not consider. In this study, due to data availability issues, we follow the operational definition of OECD (2014), considering the whole of ISIC rev.4 division 26 (Manufacture of computer, electronic and optical products) plus section J.

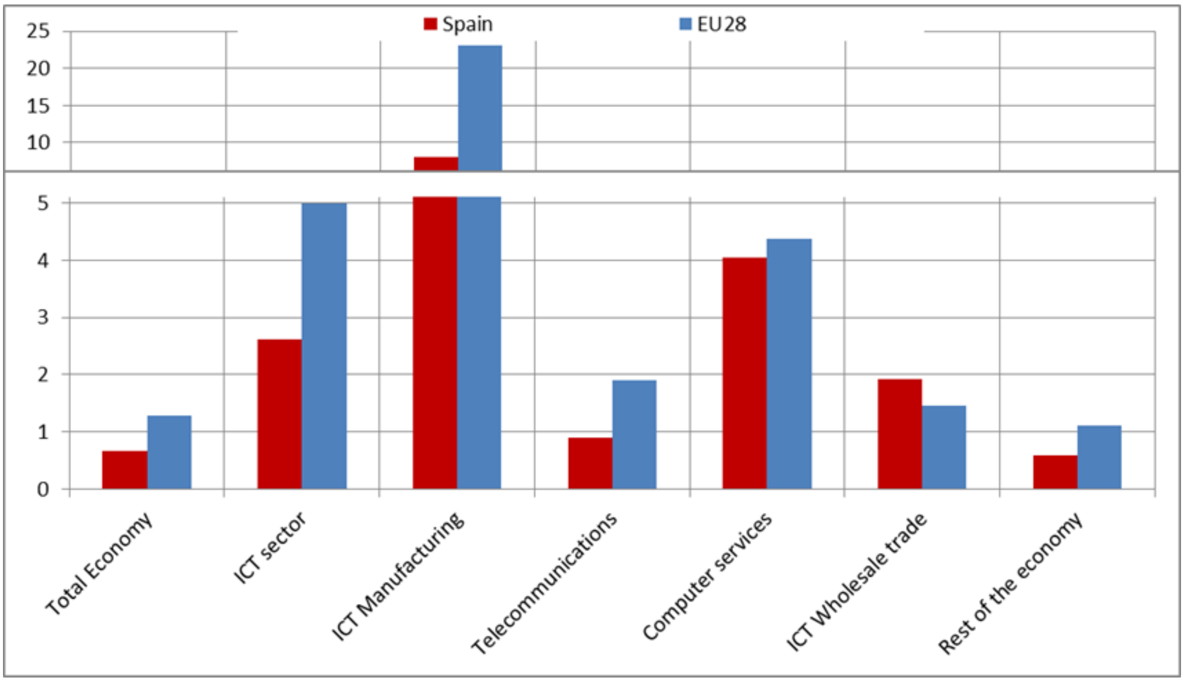
Figure 1: Value added of ICT industries as a share of GDP, EU Member States and main world producers, 2013 and 2006, percentage values



Source: JRC-IPTS. PREDICT Project database 2016
Note: data for Japan and Canada refer to 2012

The R&D intensity of the ICT sector also varies greatly. In Spain, its share in total BERD is about 14.5%, but its R&D intensity is only 2.6% of value added: about half the EU average, although it follows a similar pattern (Figure 2).

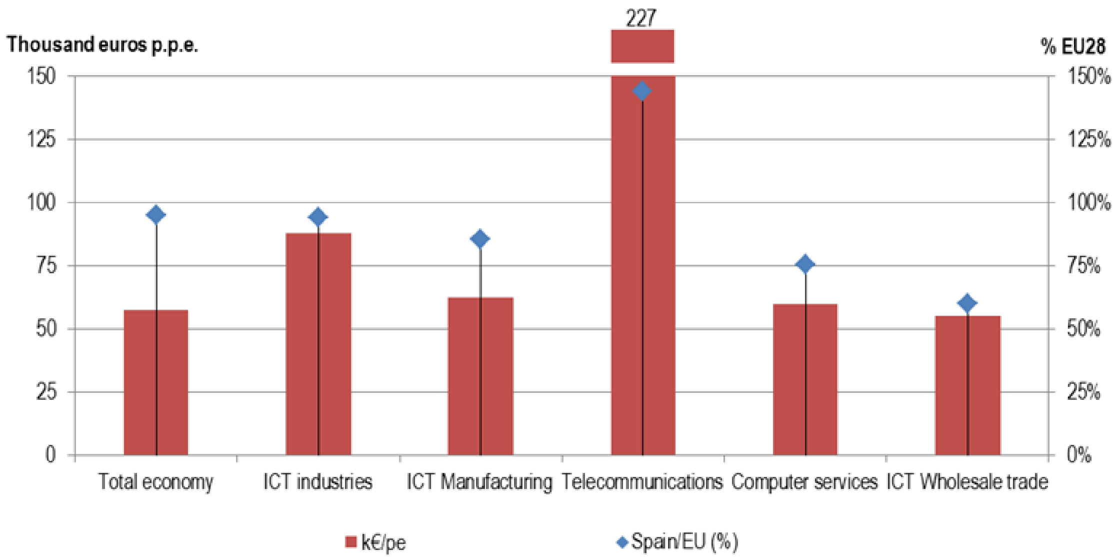
Figure 2: BERD intensity (% share on value added) in Spain and the EU28 by industry, 2013



Source: JRC-IPTS. PREDICT Project database 2016

The higher-than-average propensity to perform innovation activities by enterprises in the ICT industries is explained by particularly important differences in product innovation (supposedly more directly related to R&D activity) and for the more complex "mixed modes" of innovation, which include joint product and process innovations and joint technical (product/process) and non-technical (organisational or marketing) innovations (Figure 3).

Figure 3: Labour productivity in the Spanish economy and in ICT industries: thousand euros per person employed and percentage values versus EU28, 2013



Source: JRC-IPTS. PREDICT Project database 2016

The influence of R&D and innovation performance on productivity in individual industries is affected by other elements, including notably their capital intensity ratios. Within the ICT sector, this is particularly evident for the case of telecommunication services (Figure 4).

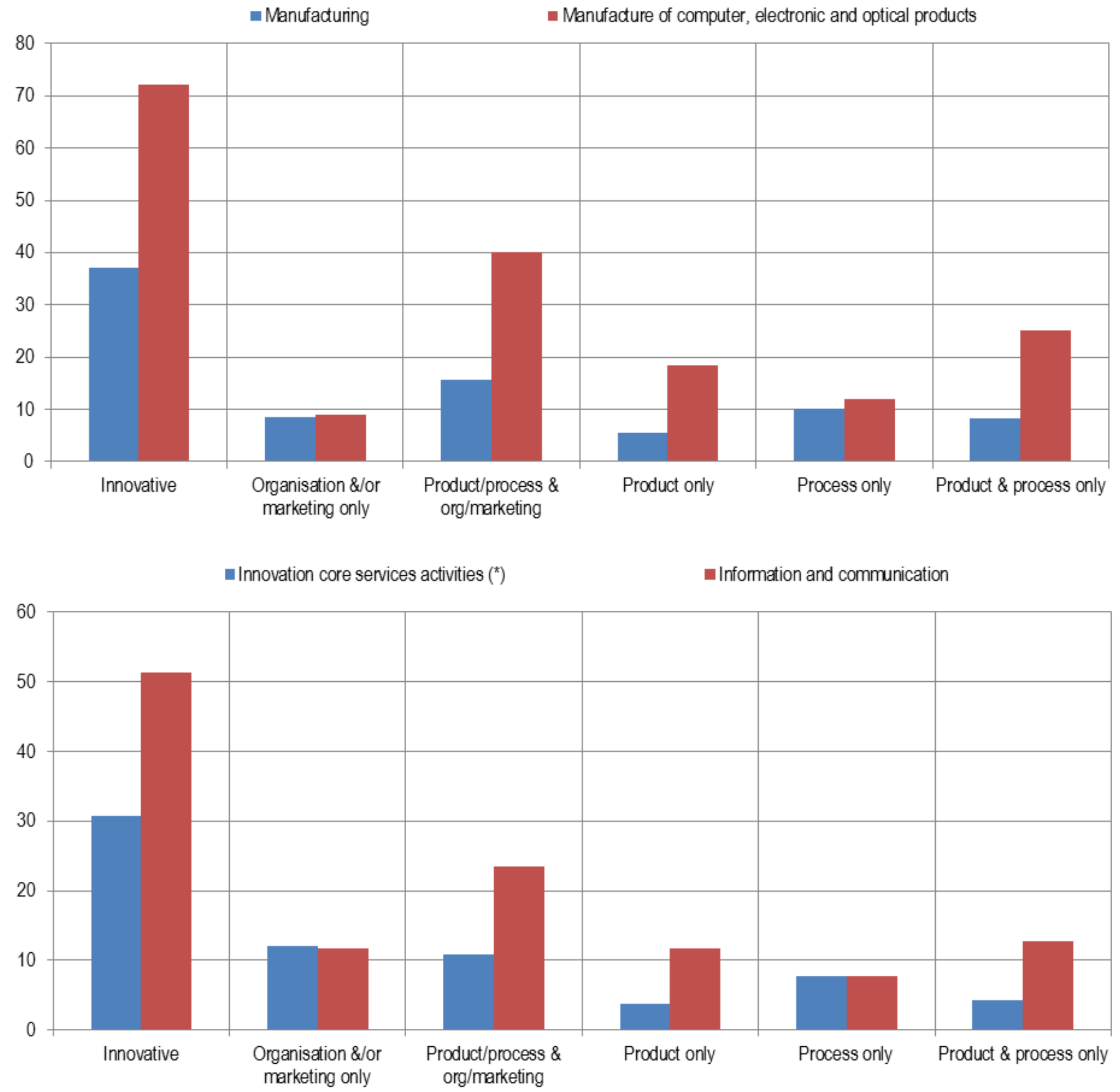
For the purpose of this report, it is also useful to recall other elements directly or indirectly associated with ICTs which are deemed to impact on the level and dynamics of innovation and productivity. Indeed, due to the fact that ICTs constitute a *general purpose technology (GPT)*, many studies have shown that their pervasive use in the economy has enabled productivity gains outside the ICT sector itself and that they play a role as an *enabler* of innovations.[3]

Growth accounting literature shows the importance of ICT capital and intangible ICT-related assets (including skills) in determining productivity. It should also be remembered that ICTs contribute to the (price) effectiveness of other types of equipment in which they are increasingly embedded. ICT industries themselves are intensive users of ICT capital: combining the five EU countries for which more detailed industry-level data are available (the Czech Republic, Finland, France, Italy and the United Kingdom), Information Industries (ICT manufacturing and *Information and Communication Services*) together absorb slightly less than 30% of total ICT-related

[3] In his early analysis on GPT impacts, Rosenberg (1982) refers this concept as "innovational complementarities" when the incremental productivity is created in downstream sectors as a results of innovation in the technology sector.

assets, which in turn represent almost 50% of total investment in these industries in 2013 (up from about 40% in the year 2000).

Figure 4: Innovation behaviour of enterprises in information and communication industries compared to manufacturing total and innovation-core services (*) in Spain: percentage shares of innovators, by type of innovation, 2012



(*) Includes NACE Rev. 2 sections & divisions 46-H-J-K-71-72-73, corresponding to wholesale trade, logistics, information and communication, financial, technical and scientific service activities

Source: Eurostat, Community Innovation Survey (CIS-8)

Since the seminal work by Crépon, Duguet and Mairesse (1998), many studies have analysed the relationships between R&D, innovation and productivity. They use a similar analytical framework, referred to as the "CDM" model approach (taking the initials of the above authors). Results share some commonalities but depend on the focus and the object (reference population) of the analysis. Examining the characteristics and findings of these studies is not the remit of the present report (for a review, see Hall, 2011). However, it is worth recalling some of the most recent works that address some of the aspects treated here, i.e. the determinants of innovation, R&D behaviour, and productivity.

The relationship between R&D and innovation is quite straightforward (considering that the aim of R&D performance is to achieve innovations, mostly of a technical nature). Other common determinants of innovative activity include cooperation, export orientation and foreign ownership[4] (Crespi & Zuniga, 2012; Gazaniol, 2012; Resende, et al., 2014; and, with a specific focus on inter-institutional R&D collaboration, Lee, et al., 2016; Maietta, 2015), the industry life cycle (Tavassoli, 2015), market structure and degree of competition (Blazsek & Escribano, 2016), the role of tacit knowledge (Romero, 2014), and the structure of labour markets (Wachsen & Blind, 2016). Coad et al. (2016), who also used the PITEC database for the period 2004–2012, found that the returns on R&D effort (intensity) are more unevenly distributed for young firms than for their older counterparts, after controlling for other variables. Complementarities between different "families" of innovation activities and within them are also well studied, with conclusions that are not always obvious.[5] On productivity, recent studies found that innovative firms are more likely to be more productive, although results also tend not to be straightforward.[6]

With regards to the CDM model commonly used to investigate this issue, Hall (2011) presented a thorough summary based on several multi-country multi-sector analyses, with several caveats that should be taken into consideration. For example, the most widely available and used measures of innovation consist of dichotomous variables. These are meant to portray the performance of individual types of innovation but can hardly capture actual innovative activity. Results are therefore often counter-intuitive or inconclusive. Additionally, market structure also plays an important role. When companies perform both product and process innovations, it is often found that the result is negative for process innovation and positive for product innovation. This may indicate that firms are operating in the inelastic portion of their demand curves and that revenue productivity is enhanced mainly by the introduction of new and improved products, and not by efficiency improvements in the production process. Hall (2011) also acknowledges the difficulties of including organizational innovation, due to the multi-collinearity of the various innovation variables.

Taking these considerations into account, this study introduces some novelties:

i) the focus on the information industries, which allows us to see the drivers and barriers of innovation and the contribution made by different types of innovation on productivity in this R&D-intensive sector;
ii) instead of considering innovation in generic terms or focusing only on a particular type of innovation, the study also investigates patterns of innovation activity, taking into account individual as well as joint technical (product-process) and non-technical (organisational-marketing) innovations and the more complex "mixed mode" of innovation (technical and non-technical). Enterprises in the information industries

[4] Instead, Sun and Du (2010) found that the transfer of foreign technologies and foreign investment did not have any significant impact on product innovation in China's high-tech manufacturing industries. Chudnovsky et al. (2006) came to a similar conclusion in the case of Argentina.

[5] In this respect, Jha and Bose (2015) found that process innovation positively impacts on product innovation but not vice versa. Hervas-Oliver et al. (2015) suggest that process innovations strengthen the impact of organizational innovation. Ballot et al. (2015) found conditional complementarities between product and process innovations and between organizational and product innovations, but no complementarities between all three forms of innovation.

[6] See, for instance, Colombelli et al., (2013) for France; Harrison et al., (2014) for France, Germany, Spain and the UK; Raymond et al. (2015) for France and the Netherlands; and Hashi and Stojčić (2013) for both the mature market economies of Western Europe and the advanced transition economies of Central and Eastern Europe.

are e more eager to perform this last mode of innovation than their peers in manufacturing and service activities, in Spain and in other countries (see OECD, 2014). This type of analysis is still missing from the existing literature as summarized by Hall (2011).

Against this background, this paper answers three inter-related research questions:

i) what are the most decisive factors that determine R&D in Spanish information industries?

ii) how does R&D activity affect innovation in its different manifestations, and in particular as regards the complementarity of the different types of innovation?

iii) what is the relationship between innovation and productivity, taking into account innovation complementarities?

The specific characteristics of our case study – notably the broad diffusion and high rates of actual R&D activity, and high shares of product and of *mixed mode* innovators – should affect results. In particular, we expect a strong positive impact of firm strategies related to technical innovation activities (particularly product innovations) on R&D performance and, in turn, of the predicted R&D on actual technical innovations (both product and process). Conversely, barriers to innovation are expected to be scarcely relevant to its effective performance, given the observed levels of R&D expenditure and innovation activity. Also, the impact of innovation on productivity is not expected to be great or straightforward. We expect to find complementarities between and within innovation families, given the high shares of mixed mode innovators. The features of this study should allow us to explore them.

2. Model and estimation

This section explains the model used to address the role of drivers for R&D, barriers to innovation and the relationship between innovation and productivity in the Spanish ICT-producing sector. It also looks at the different methodologies employed for estimation.

As in most of the empirical literature which looks at the relationship between R&D, innovation and productivity, we rely on the well-known CDM model (Crépon et al., 1998). Briefly, since the model has been explained in depth elsewhere (see Hall, 2011 and references therein), this model is essentially composed of three main blocks:

i) the decision to conduct R&D activities, along with the intensity of the R&D undertaken by those firms that perform R&D is analysed simultaneously (*decision* and *intensity equations*, respectively);

ii) the probability of introducing innovations, given the R&D effort estimated from the first block (the innovation equation); and

iii) the estimated innovation output and other explanatory variables enter into a reduced-form labour productivity equation.

In its general formulation, the model is static and unidirectional, since it does not consider the impacts of productivity on R&D effort or innovation outputs. On the other hand, the CDM model permits us to overcome issues of endogeneity of R&D in the innovation equation and of innovation in the productivity equation, as well as possible bias in the selection of the R&D performers. Empirical studies estimated the CDM model equations either jointly, by asymptotic least squares, or sequentially by means of instrumental variables. In this latter case, the predicted value of the endogenous variable in the outcome equation is an explanatory variable in the equation of the following analytical step[7].

In order to take into account selection bias issues in the first block, the paper will follow a sequential estimation strategy. Also, unlike the majority of studies, conducted using cross-section data due to sample features in most innovation surveys, our database has a panel nature that is expected to improve the estimation. Finally, the paper also attempts to investigate the role of different types of innovation in productivity, contrasting the impact of *any* innovative activity, as in the model proposed by Hall et al. (2013) with the specific influence of technical (product/process), non-technical (organizational/marketing) and joint ("mixed mode") innovations, and also of product, process and joint product-process innovations, all of which are considered separately.

2.1 The R&D decision and intensity equations

The first block of the model tackles the firm's R&D activities, i.e. the decision to engage in R&D and, in this case, the R&D effort (measured by the ratio of R&D expenditure over sales). The *decision equation* for firm *i* at time *t* can be specified as follows:

$$[1] \qquad D_{it} = \begin{cases} 1 & \text{if} \quad \delta Z_{it} + \varphi_i + \varepsilon_{1it} > 0 \\ 0 & \text{if} \quad \delta Z_{it} + \varphi_i + \varepsilon_{1it} < 0 \end{cases}$$

Where D_{it} is an (observable) dichotomous variable, that takes the value 1 if the firm decides to perform R&D activities and 0 otherwise, Z_{it} is a set of explanatory variables, φ_i

[7] Musolesi and Huiban (2009) have demonstrated that differences in the results derived from sequential instrumental variables estimation and maximum likelihood estimation are not important. Results are robust to the estimation method, if endogeneity and selection bias are taken into account in the first block (Mohnen and Hall, 2013).

that captures unobserved firm heterogeneity, and ε_{1it} is the error term. The *intensity equation* is defined as:

$$[2] \qquad R\&D_{it} = \begin{cases} \beta X_{it} + \alpha_i + \varepsilon_{2it} & \text{if } D_{it} = 1 \\ 0 & \text{if } D_{it} = 0 \end{cases}$$

Where X_{it} is the set of determinants for R&D intensity, α_i captures again the unobserved firm heterogeneity, and ε_{2it} is an error term.

In both equations, Z_{it} and X_{it} include the main characteristics of the enterprise, such as its size (in log), age (in log), ownership (foreign vs. domestic, belonging to a group), and public support (with a lag). In the intensity equation, the vector X_{it} also includes a dummy variable to control for the fact that the firm cooperates in R&D with other organisations, and variables that capture the *importance* firms attach to different types of innovation (not the actual performance), considered separately: only product innovation, or only process innovation, and also innovations to reduce environmental impacts and/or to meet regulations.

The two equations that compose the first block are estimated simultaneously using the full parametric random-effects dynamic panel data sample-selection estimator proposed by Raymond et al. (2007)[8]. This Maximum Likelihood estimator solves two main difficulties that characterise this system of equations, i.e. the presence of individual effects and the consideration of the initial conditions in a dynamic setting. The procedure relies on random effects, since fixed effects are unfeasible given that the panel consists of a large number of individuals (firms) and a small number of time observations[9]. To overcome the initial conditions problem due to the choice of random effects, the suggested procedure specifies a distribution for the individual effects depending on the initial conditions and on strictly exogenous explanatory variables (Wooldrige, 2005).[10]

2.2 The innovation equation

The second block connects research activities undertaken by firms, and its intensity, to innovation output. The *innovation equation* can be written as

$$[3] \qquad INN_{it} = \gamma\widehat{R\&D}_{it} + \omega W_{it} + \theta_i + \mu_{it}$$

Where: the indicator for innovation INN_{it} takes the value 1 if the firm *i* introduces an innovation in period *t* and 0 otherwise; $\widehat{R\&D}_{it}$ is the predicted R&D intensity estimated in equation [2] of the first block, to avoid potential endogeneity problems; W_{it} is a vector of variables portraying other determinants of innovation (size, and dummy variables portraying belonging to a group and perceived barriers to innovation related to financial constraints, access to knowledge and market conditions)[11]; θ_i captures firm

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8 For an example of the application of this estimation procedure, and a more detailed explanation of how the method works, see Costa-Campi et al. (2014).

9 Indeed, estimating a large number of dummy variables for individual effects when the number of periods is small works only under the assumption of strict exogeneity of the explanatory variables, ruling out the inclusion of lagged dependent variables as explanatory variables (Neyman and Scott, 1948).

10 This procedure yields consistent estimates of the parameters under the assumption of correct specification of the distribution of errors, is easier to implement and more flexible to be applied to a wide range of nonlinear dynamic panel data models than the approach suggested by Heckman (1981).

11 These include, respectively, (a) lack of internal or external resources to finance innovation activities or high costs, (b) lack of qualified personnel or of information on relevant

characteristics different from the variables included in W; and μ_{it} is an error term. In the empirical specification, INNit is multidimensional, since there are many types of innovations. Traditionally, the distinction has been between product and process innovations. Lately, organisational and marketing innovations have also been considered. Here, we distinguish between these two types of innovations. Hence, the second block will be formed of two equations, one for each type of innovation considered.

The innovation equations in the second block – traditional and recent innovations – are estimated separately, using a random effects probit model. In addition, and in order to account for possible systematic correlations between the decisions to perform different types of innovative activities, we estimate a bivariate probit model with binary equations for each innovation outcome.[12]

2.3 The productivity equation

The last block of the CDM model relates innovation outputs to productivity. As in most papers in the literature (see Hall, 2011 for a survey), our dependent variable is labour productivity, and the equation can be stated as follows:

$$[4] \qquad P_{it} = \vartheta \widehat{INN}_{it} + \rho Y_{it} + \sigma_i + \tau_{it}$$

Here, P_{it} is labour productivity, $\widehat{INN}_{it}$ is the innovation output predicted with the innovation equation [3], Y_{it} is the set of explanatory variables which include labour, physical capital (capital stock or investment, per employee) and age of the firm, σ_i captures firm unobserved heterogeneity and τ_{it} is an error term. More appropriate measures of productivity such as value added per employee (or per hour worked), or total factor productivity, cannot be computed because of a lack of information on hours worked, value added, and sufficient data to compute long capital stock series in the database. Controlling for unobserved firm heterogeneity, however, can be expected to absorb much of the differences derived from firms' unobserved characteristics. We follow Hall et al. (2013) and also include the predicted R&D effort from the first block as a determinant of productivity. To be consistent with the estimation procedures of the first and second blocks, we use a random effects estimator to assess the relationship between innovation and productivity.

technologies or markets, and (c) the fact that the market be dominated by an incumbent and/or uncertainty on demand for innovative products.

12 In this case, the only possibility of carrying out the estimations is to use pooled data and therefore it is not possible to control for individual effects.

3. Data

In this study, the empirical analysis is based on data from the Spanish Technological Innovation Panel (PITEC) for the period from 2004 to 2013. PITEC is a collaborative data collection conducted by the Spanish National Statistics Institute (INE) and the COTEC Foundation, which aims to provide data to the Community Innovation Survey (CIS). The survey is carried out annually following the guidelines of the OECD's Oslo Manual. The PITEC presents comprehensive and detailed information on the characteristics of Spanish firms and their innovative activities. Overall, the dataset provides exhaustive information for more than 12,000 firms for the period 2003–2013 and has been frequently used to carry out empirical analyses on innovation in general (e.g. Barge-Gil, 2010; De Marchi, 2012) and also for specific sectors (e.g. Costa-Campi, et al., 2014 focus on innovation in energy).

The sample from the Spanish PITEC survey data in *Information industries* amounts to over 1000 firms per year. For 2012, this sample corresponds to about 1.7% of the population of firms recorded in Spanish Structural Business Statistics. Coverage is about 5% of the total population in ICT manufacturing, about 0.9% in Telecommunications, and about 1.5% in IT, content and media services. However, due to the survey's design, firms in the sample are on average much larger than the reference population, so that coverage stands at about 39% of the total for employment[13] and reaches 70% for sales[14]. This implies that firms in the sample are far more productive than the average when measured on sales. It also implies that innovators tend to be overrepresented in the sample with respect to the reference population. The skewedness of the PITEC sample towards larger enterprises is also reflected in a higher proportion of companies performing innovation than in the official results from the *Community Innovation Survey*, across all industries and innovation types considered[15].

Finally, we used *total* R&D expenditure in the study, including expenditure on R&D activity performed (by subsidiaries or third companies) abroad. This was a major departure from BERD data in official statistics, which only refer to R&D performed *in the economy*. This also had an impact on R&D effort in the telecom sector, with a coverage much higher than total BERD[16] (Table 1). Combining all years, enterprises considered in the study on average employed 184 workers, had been operating for 17 years and devoted 11% of their sales to R&D activities[17] (Table 2).

[13] Up to 80% for the case of Telecommunications which, however, do not impact much on the total.

[14] Up to 82% for Telecommunications and just above 60% for ICT manufacturing and IT services.

[15] For instance, product innovations in our sample are performed by 62% of enterprises in ICT manufacturing against 44% in CIS, 51% in Telecommunications against 24%, and 45% against 24% in IT and CM services.

[16] For the case of Telefonica, for instance, the centres of R&D are also located in Tel Aviv, Santiago, Sao Paolo and London.

[17] In this respect, for instance, Costa-Campi et al. (2014) reported an R&D effort in the Spanish energy industry of 1.7% using the same database, although for a shorter time period.

Table 1 – Characteristics of the study-sample vs. the reference population of enterprises for 2012

Industries	Number of firms			Employment					
				Total			*Average*		
	Sample	Pop.	Coverage	Sample	Pop.	Coverage	*Sample*	*Pop.*	*S/P ratio*
ICT manufacturing	234	5,077	4.6%	14,680	83,571	18%	*63*	*16*	*3.8*
Telecommunications	51	5,807	0.9%	45,324	56,530	80%	*889*	*10*	*91.3*
IT+CM services	721	47,234	1.5%	125,696	339,345	37%	*174*	*7*	*24.3*
Total	**1,006**	**58,118**	**1.7%**	**185,700**	**479,446**	**39%**	***184.59***	***8.25***	***22.4***

Industries	Sales (€ million)						R&D expenditure (€million)					
	Total			*Average*			Total R&D			*Average*		
	Sample	Pop.	Coverage	*Sample*	*Pop.*	*S/P ratio*	Sample	Population	Coverage	*Sample*	*Population*	*S/P ratio*
ICT manufacturing	2,200	3,521	62.5%	*9*	*1*	*14*	137	180	76%	*0.6*	*0.04*	*17*
Telecommunications	26,972	32,939	81.9%	*529*	*6*	*93*	566	154	367%	*11.1*	*0.03*	*418*
IT+CM services	24,467	40,165	60.9%	*34*	*1*	*40*	387	665	58%	*0.5*	*0.01*	*38*
Total	**53,639**	**76,624**	**70.0%**	***53***	***1.3***	***40***	**1,090**	**999**	**109%**	***12.22***	***0.08***	***161***

Industries	Proportion of companies performing innovation							
	Product		Process		Organisational		Marketing	
	PITEC	CIS	PITEC	CIS	PITEC	CIS	PITEC	CIS
ICT manufacturing	62%	44%	45%	37%	44%	31%	43%	42%
Telecommunications	51%	24%	51%	20%	57%	24%	49%	28%
IT+CM services	45%	24%	34%	20%	41%	21%	33%	29%
Total	**53%**	**31%**	**43%**	**26%**	**47%**	**25%**	**41%**	**33%**

Sources: PITEC (sample), Eurostat (reference population), Eurobase (Structural Business Statistics and Community Innovation Survey - CIS)

Table 2 – Summary statistics for the study sample

	Obs.	Mean	Std. Dev.	Min	Max
Characteristics:					
R&D effort	10,632	10.9	17.5	0	99.7
R&D decision	10,632	0.657	0.475	0	1
Size	10,632	184.3	843.0	1	14,080
Age	9,275	17.0	12.2	0	147
Public funds	10,632	0.394	0.489	0	1
Group	10,632	0.338	0.473	0	1
Foreign capital	10,632	0.117	0.321	0	1
Cooperation	8,845	0.373	0.484	0	1
Capital per employee (000)	6,261	223.5	2622.7	0	81,300
Investment per employee (000)	10,632	7.2	84.2	0	4,602
R&D drivers:					
Both product and process	8,844	0.363	0.481	0	1
Only product	8,844	0.356	0.479	0	1
Only process	8,844	0.041	0.198	0	1
Environmental	8,844	0.093	0.290	0	1
Norms and regulations	8,844	0.159	0.366	0	1
Innovation:					
Both product and process	10,632	0.375	0.484	0	1
Only product	10,632	0.257	0.437	0	1
Only process	10,632	0.099	0.299	0	1
Only organisational	10,632	0.166	0.372	0	1
Only marketing	10,632	0.044	0.210	0	1
Technical innovations	10,632	0.731	0.444	0	1
Non-technical innovations	10,632	0.424	0.494	0	1
Barriers:					
Financial	10,632	0.216	0.412	0	1
Knowledge	10,632	0.010	0.099	0	1
Market	10,632	0.134	0.340	0	1

In the study, we control for existing differences within the *Information industries* aggregate in terms of capital intensity, size, innovation modes and intensity, R&D performance, among others. We distinguish between enterprises in ICT manufacturing, telecommunications and IT and Content and Media services by means of dichotomous dummies.

Databases with information at the firm level tend to be noisy, biased towards large firms and include outliers. To avoid biased results, the data have been cleaned by including only privately-owned companies and removing outliers in terms of their R&D effort and productivity[18]. Also, following the recent literature on barriers to innovation (see for instance Blanchard et al., 2013 and Pellegrino and Savona, 2013), the analysis focuses exclusively on potential innovators[19]. We end up with a panel including 1,794 firms and 10,632 observations, i.e., on average every firm is present in the data for around 6 years. While only 1.5% of the observations correspond to singletons (firms that only appear one year), 18% of observations come from companies that are present in the database during the whole period 2004-2013.

18 Companies with a ratio of R&D expenditure over sales above 100% were removed from the sample, as well observations with very large labour productivity values (the top 1%). Data for 2003 were also excluded, since many variables related to innovation are missing for that initial year.

19 To this end firms that (a) have not innovated *and* declared that (b) they do not to perceive any obstacle to innovation, *and* that (c) they do not need to innovate, were also removed from the sample.

4. Results and discussion

The empirical analysis hereunder to some extent confirms the expected results and hypotheses outlined in Section 1 above, qualifying them and adding other –sometimes unexpected– elements. On the other hand, it also shows that the model we used can only give partial and often contradictory answers to the issues we addressed. In more detail:

Drivers of R&D performance and of R&D effort: the decision to perform R&D depends on firms' characteristics. For those firms that undertake R&D activities, their performance is also influenced by drivers related to perceptions of the relevance of the different types of innovations. The results of the simultaneous estimation of these two equations are shown in Table 3. The main results are discussed below.

Table 3: First stage: the decision to perform R&D and the R&D effort

	R&D effort	Decision to undertake R&D
Size (logs)	-0.434***	0.188***
	(0.0133)	(0.0194)
Age (logs)	-0.0797**	-0.325***
	(0.0378)	(0.0574)
Public funds (t-1)	0.318***	0.857***
	(0.0329)	(0.0497)
Group	-0.0633	-0.348***
	(0.0385)	(0.0633)
Foreign capital	0.0266	-0.210***
	(0.0497)	(0.0710)
Cooperation	0.124***	
	(0.0287)	
Objectives:		
Both product and process innovations	0.149***	
	(0.0389)	
Product innovation (exclusive)	0.227***	
	(0.0368)	
Process innovation (exclusive)	-0.0187	
	(0.0735)	
Environmental impact	0.0292	
	(0.0489)	
Norms and regulations	0.0342	
	(0.0427)	
Constant	3.273***	1.892***
	(0.109)	(0.194)
Observations	7,331	10,632
Tests of sample selection and individual effects:		
$\rho_{a_1 a_2}$	0.127***	
	(0.0399)	
$\rho_{\varepsilon_1 \varepsilon_2}$	-0.566***	
	(0.0706)	
σ_{a_1}	0.0484**	
	(0.0239)	
σ_{a_2}	-0.392***	
	(0.0191)	

Note: Raymond et al. (2007) parametric random-effects panel data sample-selection estimator. Both $\rho_{a_1 a_2}$ and $\rho_{\varepsilon_1 \varepsilon_2}$ are statistically different from zero, indicating that selection bias correction is needed. In addition, both σ_{a_1} and σ_{a_2} are also statistically different from zero, indicating the presence of significant individual effects. These tests validate the chosen estimation procedure. Standard errors in parentheses and *** indicates significance at 1%, ** indicates significance at 5% and * indicates significance at 10%.

a. **The effect of the perceived importance of innovation** on the effort devoted to R&D is *relevant in the case of product innovation* (as expected); *both stand-alone and combined* with process innovation. However, in the case of *process innovation alone it is not as relevant* (and, by the way, process innovation is very rare in our sample), as the *other innovation-related drivers considered* (norms, environment).

b. **Other drivers and controls** include:

   - **The previous availability of public funds**, which plays an important role in both the decision to undertake R&D and the R&D effort. This may be an argument in favour of R&D subsidies. It should be noted that in almost half the cases, companies which received public funds also engaged in R&D cooperation (see below).
   - **Cooperation in R&D,** which can only be observed for actual R&D performers, is significantly correlated to their R&D effort, and co-operators also have comparatively higher chances of getting public funds (more than 70% of the cases observed).
   - **Being young** seems to be a plus in both the decision to undertake R&D and the R&D intensity on sales, controlling for relevant variables.
   - **Being local and independent**: companies that do not belong to a group and with no foreign participation are more likely to undertake R&D. The fact that most foreign-participated companies also belong to a group (belonging to a group here acts as a control variable, in view of task differentiation between companies in a group) to some extent indicates that subsidiaries of MNCs in Spain's Information industries are less likely to put their R&D here. On the other hand, and as expected, R&D performers in groups and/or foreign participated companies tend to be specialised and the influence of these elements on effort is positive, though not significantly so.
   - **Size**: as expected, larger companies are more likely to undertake R&D, but their effort is significantly less than that of smaller companies.

<u>Drivers of innovative activity:</u> explanatory variables include the R&D effort predicted via the *intensity equation,* and controls. The analysis looks into each family of innovations (technical and non-technical) separately (both gross and net of the effect of other innovation types by means of dummies). It also looks at the linkages between technical and non-technical innovations in terms of statistical complementarity estimated with a bivariate probit model (Table 4).

Table 4 - The innovation equations:

A. Technical innovations

	Joint product & process	Only product	Only process	incl. controls for non-technical innovations: Joint	Only product	Only process
Predicted R&D effort	0.134***	0.117***	0.0460***	0.117***	0.123***	0.0468***
	(0.0060)	(0.0052)	(0.0044)	(0.0059)	(0.0052)	(0.0045)
Barriers:						
Financial	0.00877	-0.00883	0.00564	0.0125	-0.0109	0.00553
	(0.0103)	(0.0099)	(0.0076)	(0.0105)	(0.0099)	(0.0076)
Knowledge	-0.0332	0.00818	0.0409*	-0.0284	0.00315	0.0431*
	(0.0382)	(0.0377)	(0.0247)	(0.0406)	(0.0380)	(0.0246)
Market	0.02	0.00558	-0.0187**	0.0201	0.00418	-0.0180*
	(0.0122)	(0.0115)	(0.0095)	(0.0125)	(0.0116)	(0.0095)
Controls:						
Group	0.0121	0.0149	-0.0149	0.0122	0.013	-0.0160*
	(0.0132)	(0.0125)	(0.0096)	(0.0133)	(0.0125)	(0.0096)
Size (logs)	0.0817***	-0.00218	0.0234***	0.0671***	0.00489	0.0237***
	(0.0048)	(0.0046)	(0.0035)	(0.0048)	(0.0046)	(0.0035)
Organisational innovations				0.132***	-0.0848***	0.00778
				(0.0100)	(0.0096)	(0.0073)
Marketing innovations				0.117***	-0.0221**	-0.0263***
				(0.0102)	(0.0100)	(0.0078)
Observations	10,632	10,632	10,632	10,632	10,632	10,632

Table 4 (continued)

B. Non-technical innovations

				Including controls for tech. innovations		
	Joint Org./Mkt	Organisation only	Marketing only	Joint	Organisational only	Marketing only
Predicted R&D effort	0.0781***	0.0260***	0.0214***	0.0289***	0.0203***	0.0141***
	(0.0059)	(0.0049)	(0.0032)	(0.0063)	(0.0054)	(0.0034)
Barriers:						
Financial	0.0132	-0.0162	-0.00265	0.0139	-0.0174	-0.00226
	(0.0116)	(0.0114)	(0.0066)	(0.0115)	(0.0114)	(0.0066)
Knowledge	-0.0171	-0.0561	0.013	-0.0249	-0.0568	0.0157
	(0.0435)	(0.0461)	(0.0237)	(0.0443)	(0.0459)	(0.0233)
Market	0.00654	-0.0214	0.00976	0.00107	-0.022	0.00843
	(0.0140)	(0.0138)	(0.0076)	(0.0139)	(0.0137)	(0.0076)
Controls:						
Group	-0.0169	0.00947	-0.000965	-0.018	0.00922	-0.0023
	(0.0143)	(0.0129)	(0.0076)	(0.0138)	(0.0128)	(0.0076)
Size (logs)	0.0557***	0.0395***	-0.00245	0.0299***	0.0356***	-0.0053**
	(0.0049)	(0.0041)	(0.0025)	(0.0048)	(0.0042)	(0.0026)
Product innovations				0.125***	-0.00851	0.0349***
				(0.0116)	(0.0107)	(0.0069)
Process innovations				0.168***	0.0522***	0.00162
				(0.0099)	(0.0096)	(0.0056)
Observations	8,311	8,311	8,311	8,311	8,311	8,311

Note: Random effects panel probit. Marginal effects reported. Regression includes sector dummies and time dummies to control for year-specific effects. Standard errors are in parentheses and *** indicates significance at 1%, ** indicates significance at 5% and * indicates significance at 10%.

Table 4 (continued)

C. The two innovation families

	Technical (gross)	Non-technical (gross)	Mixed mode	Technical only	Non-technical only
Predicted R&D effort	0.745***	0.351***	0.124***	0.162***	0.0983***
	(0.0144)	(-0.0143)	(0.00301)	(0.00312)	(0.00548)
Barriers:					
Financial	0.0299	0.0424	0.0104	0.0027	-0.00433
	(0.0389)	(-0.0357)	(0.00823)	(0.00812)	(0.0129)
Knowledge	0.0988	-0.107	-0.0229	0.00326	-0.0691
	(0.164)	(-0.147)	(0.0286)	0.0301	(0.0479)
Market	-0.0128	-0.0506	-0.00348	0.00613	-0.0026
	(0.0462)	(-0.0428)	(0.00979)	0.00985	(0.0155)
Controls:					
Group	0.0535	-0.044	0.0135	0.0135	-0.00105
	(0.0361)	(-0.035)	(0.0101)	(0.0105)	(0.0157)
Size (logs)	0.258***	0.242***	0.0531***	0.0611***	0.0835***
	(0.0113)	(0.0111)	(0.00312)	(0.00341)	(0.00485)
Rho (ρ)	0.466***				
	(0.0244)				
Log pseudo-likelihood	-9259.4				
Wald chi2 (34)	110056.9				
Prob chi2	0.000				
Observations	10,632		10,632	10,632	8,311

Note: Columns 1 and 2: Bivariate probit Regression includes sector dummies and time dummies to control for year-specific effects; ρ is a correlation parameter that provides information about the covariation of the error terms, assuming normality of the error terms. Columns 3 to 5: Regression includes sector dummies and time dummies to control for year-specific effects. Standard errors are in parentheses and *** indicates significance at 1%, ** indicates significance at 5% and * indicates significance at 10%.

a. The predicted R&D effort is significantly positive for the prediction of all types of innovation and all possible associations (within the same family and between them), also net of relevant controls. Overall, the impact on the performance of both technical and non-technical innovations is similar, with a comparatively higher marginal effect for product innovations in the first group and for organisational innovation in the latter. Impacts on joint (product-process; organisational-marketing) and on *mixed-mode* innovations (technical-non technical) are also high. Results point at a strong complementarity between the two families of innovations (□=.47 in table 4c).

b. Barriers to innovation do not appear to have any relevant impact, except in the case of process innovation, where market features (strong incumbents, uncertainty of demand) constitute a *deterring* barrier (negative sign). Specific knowledge is a *revealed* barrier, which can be appreciated only when the activity is underway (positive sign).

c. Size is relevant for all types of innovations, except for product innovations alone (SMEs are as likely as larger companies to launch new products). It is interesting to note that the marginal effect of size is higher for joint innovations within the same family than for stand-alone types of innovations, which indicates that multiple type and complex modes of innovation are more likely to be performed by larger companies.[20]

Drivers of labour productivity. This third stage of analysis, based on the CDM model *productivity equation* approach, considers different specifications:

- the occurrence of *any type* of innovation (Table 5A) as in Hall et al. (2012), which is also mimicked in terms of the other variables considered, to allow for some comparability of results;
- the two technical (product and process) and the two non-technical (organisational and marketing) innovations at the individual level gross of other occurrences (Table 5B), these innovation families separately (Table 5C) and combined (Table 5D), including the specific case of mixed mode innovators;
- additionally, given limitations in the computability of capital stock from the available figures for aggregate investments available in the dataset[21], results for each regression are provided using capital stock and, in parallel and with a larger sample, using investment as a proxy.

Results are synthesised in Table 5:

[20] It should be noted that controls in Tables 4A and 4B for each innovation type show a (mild) negative relationship between product and organisational innovations, and that in Table 4D the predicted R&D effort has a comparatively higher impact on non-technical innovations: these apparent inconsistencies with the assumption that that R&D is mostly finalised to technical (notably *product*) innovations and the finding that the two families of innovations are complementary can be explained based on enterprise characteristics. Indeed, product innovations are easily achieved also by SMEs (also net of R&D performance – see *infra*), while organisational innovations are more an affair of larger (and more R&D prone) companies.

[21] The computation was performed using the perpetual inventory approach.

Table 5 – The drivers of labour productivity (dependent variable: (log) sales/employee)

A. Any type of innovation

Any type of innovation	0.0436 (0.0386)	0.391*** (0.143)	0.114*** (0.0286)	0.422*** (0.108)
Predicted R&D effort		-0.0898** (0.0355)		-0.0795*** (0.0270)
Capital per employee (log)	0.146*** (0.0101)	0.147*** (0.0101)		
Investment per employee (log)			0.0146*** (0.00168)	0.0151*** (0.00168)
Employment (log)	-0.138*** (0.0310)	-0.174*** (0.0341)	-0.209*** (0.0213)	-0.239*** (0.0237)
Employment squared (log)	0.0129*** (0.00376)	0.0130*** (0.00376)	0.0184*** (0.00287)	0.0183*** (0.00287)
Age (log)	-0.332 (0.317)	-0.330 (0.317)	0.784*** (0.228)	0.775*** (0.228)
Age squared (log)	0.273** (0.134)	0.270** (0.134)	-0.183* (0.0968)	-0.183* (0.0967)
Constant	9.902*** (0.221)	9.858*** (0.222)	10.70*** (0.139)	10.67*** (0.139)
Observations	5,477		9,268	
Number of firms	654		1,293	
R^2 (overall)	0.181	0.183	0.0938	0.0966

B. Individual innovation types (gross)

Product innovation	0.288 (0.196)	0.559* (0.309)	0.553*** (0.153)	0.559** (0.241)
Process innovation	0.581 (0.385)	0.300 (0.457)	0.819*** (0.300)	0.809** (0.362)
Organisational innovation	-0.219 (0.290)	-0.146 (0.298)	-0.302 (0.230)	-0.301 (0.238)
Marketing innovation	-0.798 (0.586)	-0.677 (0.597)	-1.161*** (0.444)	-1.159** (0.457)
Predicted R&D effort		-0.0285 (0.0252)		-0.000630 (0.0201)
Capital per employee (log)	0.146*** (0.00996)	0.146*** (0.00993)		
Investment per employee (log)			0.0150*** (0.00168)	0.0150*** (0.00169)
Employment (log)	-0.145*** (0.0324)	-0.145*** (0.0324)	-0.218*** (0.0227)	-0.217*** (0.0227)
Employment squared (log)	0.0137*** (0.00376)	0.0138*** (0.00375)	0.0196*** (0.00288)	0.0197*** (0.00288)
Age (log)	-0.362 (0.316)	-0.357 (0.316)	0.732*** (0.228)	0.728*** (0.228)
Age squared (log)	0.287** (0.134)	0.284** (0.134)	-0.161* (0.0968)	-0.160* (0.0968)
Constant	9.962*** (0.225)	9.937*** (0.226)	10.79*** (0.143)	10.80*** (0.145)
Observations	5,477		9,268	
Number of firms	654		1,293	
R^2 (overall)	0.183	0.185	0.0955	0.0968

Note: Regressions include sector dummies and time dummies to control for year-specific effects.
Standard errors in parentheses; ***= p<0.01, ** = p<0.05, *= p<0.1

Table 5 (Continued)

C1. Technical innovations (gross)				
Both product and process	-0.404*** (0.141)	-1.296*** (0.331)	-0.288*** (0.110)	-1.120*** (0.243)
Only product	0.637*** (0.224)	-0.00487 (0.311)	0.633*** (0.171)	-0.0474 (0.246)
Only process	-0.571 (0.559)	-1.482** (0.637)	-0.0327 (0.444)	-0.852* (0.492)
Predicted R&D effort		0.171*** (0.0573)		0.164*** (0.0427)
Capital per employee (log)	0.146*** (0.00999)	0.146*** (0.00999)		
Investment per employee (log)			0.0155*** (0.00169)	0.0153*** (0.00169)
Employment (log)	-0.115*** (0.0336)	-0.0545 (0.0393)	-0.196*** (0.0238)	-0.141*** (0.0277)
Employment squared (log)	0.0146*** (0.00378)	0.0162*** (0.00382)	0.0202*** (0.00289)	0.0220*** (0.00293)
Age (log)	-0.340 (0.316)	-0.361 (0.316)	0.758*** (0.228)	0.747*** (0.227)
Age squared (log)	0.275** (0.134)	0.286** (0.134)	-0.175* (0.0966)	-0.168* (0.0965)
Constant	9.966*** (0.221)	10.17*** (0.231)	10.77*** (0.139)	10.97*** (0.148)
Observations	5,477		9,268	
Number of id	654		1,293	
R^2 (overall)	0.185	0.185	0.0980	0.0974

C2. Non-Technical innovations (gross)				
Both organisational and marketing	0.324 (0.210)	0.485* (0.256)	0.920*** (0.164)	1.067*** (0.194)
Only organisational	-0.258 (0.345)	-0.236 (0.346)	-0.867*** (0.279)	-0.829*** (0.280)
Only marketing	-0.217 (0.400)	0.165 (0.529)	-0.439 (0.300)	-0.0589 (0.402)
Predicted R&D effort		-0.0208 (0.0189)		-0.0208 (0.0146)
Capital per employee (log)	0.146*** (0.0100)	0.147*** (0.0100)		
Investment per employee (log)			0.0142*** (0.00168)	0.0145*** (0.00169)
Employment (log)	-0.154*** (0.0334)	-0.168*** (0.0357)	-0.263*** (0.0241)	-0.276*** (0.0260)
Employment squared (log)	0.0141*** (0.00388)	0.0146*** (0.00391)	0.0231*** (0.00303)	0.0236*** (0.00306)
Age (log)	-0.352 (0.318)	-0.348 (0.318)	0.720*** (0.229)	0.722*** (0.229)
Age squared (log)	0.285** (0.135)	0.283** (0.135)	-0.149 (0.0970)	-0.150 (0.0970)
Constant	9.775*** (0.239)	9.683*** (0.253)	10.38*** (0.152)	10.30*** (0.162)
Observations	5,477		9,268	
Number of firms	654		1,293	
R^2 (overall)	0.181	0.181	0.0907	0.0902

Note: Regressions include sector dummies and time dummies to control for year-specific effects.
Standard errors in parentheses; ***= p<0.01, ** = p<0.05, *= p<0.1

Table 5 (Continued)

D. Mixed mode innovators vs. technical or non-technical only				
Mixed-mode innovations	0.163** (0.0743)	0.321** (0.127)	0.299*** (0.0547)	0.350*** (0.0980)
Technical innovations only	0.0855 (0.0905)	0.244* (0.138)	0.0102 (0.0695)	0.0635 (0.109)
Non-technical innovations only	1.148*** (0.317)	1.137*** (0.317)	1.472*** (0.245)	1.466*** (0.245)
Predicted R&D effort		-0.0499 (0.0327)		-0.0163 (0.0258)
Capital per employee (log)	*0.148**** *(0.0101)*	*0.148**** *(0.0100)*		
Investment per employee (log)			*0.0150**** *(0.00168)*	*0.0151**** *(0.00168)*
Employment (log)	-0.164*** (0.0322)	-0.177*** (0.0333)	-0.249*** (0.0226)	-0.252*** (0.0233)
Employment squared (log)	0.0149*** (0.00381)	0.0149*** (0.00380)	0.0214*** (0.00292)	0.0214*** (0.00292)
Age (log)	-0.341 (0.317)	-0.335 (0.317)	0.772*** (0.228)	0.771*** (0.228)
Age squared (log)	0.281** (0.134)	0.276** (0.134)	-0.175* (0.0967)	-0.176* (0.0967)
Constant	9.780*** (0.226)	9.744*** (0.227)	10.57*** (0.142)	10.56*** (0.143)
Observations	5,477		9,268	
Number of firms	654		1,293	
R^2 (overall)	0.180	0.181	0.0899	0.0911

Note: Regression includes sector dummies and time dummies to control for year-specific effects.
Standard errors in parentheses; ***= p<0.01, ** = p<0.05, *= p<0.1

a. Innovation and R&D effort

- Performing ***any type of innovation*** (Hall et al., 2013-like specification) has a positive effect on productivity; controlling for the predicted R&D effort improves significance but in this specification this latter has a negative impact. Other controls are as expected (see below).
- When we look at ***individual innovation types*** (without individual controls for associations among them), we find a more contrasted landscape. Technical innovations are positively related to productivity but significant only when capital intensity is proxied by investment per capita, in which case marketing innovations subtract from productivity.
- Looking at ***the two families of innovations separately*** also shows that innovation *per se* is not capable of explaining productivity. Results vary, depending on the presence and relevance of latent variables. In general, *technical innovators* (without considering their behaviour for non-technical ones) are likely to be less productive than their peers, after controlling for other relevant variables. As expected, however, the predicted R&D effort in this case is positively related to performance. Probably due to correlations with the size-factor, the worst results are obtained for process and joint product-process innovations. Performers of *non-technical innovations* (without considering technical ones) are also likely to be less productive in the case of organisational innovations (partly overlapping with organisational ones). However, in this case, joint organisational and marketing innovation may have a positive impact (milder when considering capital than for the case of investment).
- Finally, looking at **innovation patterns globally**, we see that the performance of *mixed-mode innovations* (both technical and non-technical) and of *stand-alone non-technical innovations* is always positively related to productivity in a significant way. We also see that the impact of the former greatly increases when controlling for the predicted R&D effort (as expected, given its relationship to technical innovations). Stand-alone technical innovators are better off than other innovators but this relationship is weak.

b. Other drivers:

- Both ***capital stock and investment per employee*** are always significant. The use of capital stock yields a greater magnitude than investment.
- ***Employment Size*** (log) tends to be non-linearly significant (first degree negative, squared variable positive) across all types of regression, suggesting that medium-sized firms are less productive than the smaller or larger firms. The same happens for the case of ***Age*** (log) when controlling for capital intensity, while we get the opposite results when using investment. This could be the result of the weak role of investment as a proxy for capital stock, or alternatively, a sample bias due to the fact that the number of observations in the regressions including capital stock per employee is limited.

In summary, our results confirm previous findings, which suggest that the relationship between innovation and productivity is far from obvious (Hall, 2011). However, our results indicate that this is particularly true in industries characterised by high R&D performance, where the borders between the different types of innovation are fuzzy. A plausible explanation is that measurement error in the innovation variables make it difficult to find strong and consistent estimates of the impacts when these variables are entered into the productivity equation. In this respect, the absence of better measurements to identify the different types of innovation –especially when complementarities are present – will undermine our ability to identify further the intricate links between innovation and productivity.

5. Concluding remarks

In this report, we focused on a sector with high R&D performance – the Spanish information industries – to shed light on the complex link between innovation and productivity. Our results confirm some previous findings, notwithstanding the specificity of the industries considered (e.g. Crépon et al., 1998; Griffith et al., 2006; Masso & Vahter, 2008; Mairesse & Robin, 2010; Colombelli et al., 2013; Harrisson et al., 2014 and Raymond et al., 2015, among others). More specifically, R&D subsidies have a positive effect on performance (as in David et al. 2000 or Hall et al. 2013), and carried by companies which perform cooperation (Barge-Gil, 2010). Also, young firms are generally more likely to perform R&D and benefit from it (García-Quevedo et al. 2014), while MNCs in this sector seem to consider Spain primarily as a market, rather than an R&D hub.

The analysis of innovation drivers confirms the R&D-innovation nexus for all types of innovation, and a strong complementarity between the two families of innovations is also observed. Perceived barriers have some impact on process innovations: market conditions can deter innovation, knowledge barriers are revealed as firms doing more innovation declare they are more concerned about lack of appropriate knowledge (Coad et al, 2014). For SMEs, product innovation is more accessible than other types.

The analysis of the innovation-productivity conundrum reveals that the links are not at all obvious and that the results strongly depend on the way we model the relationship. Hall (2011), in her survey of the literature suggests a similar argument. In our case, we were able to consider more complex innovation patterns. This allowed us to show that companies which perform different types of innovations simultaneously (mixed mode) or which focus only on non-technical (marketing, organisational) innovations are likely to be more productive. In addition, we should also point out that the relationship between innovation and productivity is necessarily influenced by the context in which the firms manoeuvre – both institutional and macroeconomic environments. Hence, noticeable differences across countries and/or sectors are to be expected in the relationship between innovation and productivity.

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