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2012

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**Documentos de Trabajo**
**N.º 1219**

BANCO DE **ESPAÑA**
Eurosistema

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(*) This draft: 28 March 2012. We thank Carmen Martínez for her help with the construction of the proxy for credit constraints. For useful comments and discussions, we also thank Nicolas Berman, Gilbert Cette, and seminar participants at CONCORD 2011, Banco de España, IVIE-Universidad de Valencia and Universidad Autónoma de Barcelona. Furthermore, the authors are grateful to Belén González from the Instituto Nacional de Estadística (INE) for kindly sharing microdata from the PITEC database. The opinion and analyses herein are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España.

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Documentos de Trabajo. N.º 1219
2012

ISSN: 1579-8666 (on line)

**Abstract**

This paper tests the opportunity-cost theory using a panel of Spanish firms during the period 1991-2010. Under this theory, productivity-enhancing activities, such as R&D investment, should increase during downturns because of the fall in their relative cost – in terms of forgone output –. This would imply that business cycles may have a (positive) long-term impact on productivity growth. In the spirit of Aghion *et al.* (2007) we allow the impact of the cycle on R&D to vary between firms with different access to credit, finding that credit constraints may reverse the countercyclicality of R&D, even if it is optimal for them. We go one step further and explore whether other productivity-enhancing activities, like on-the-job training and the purchase of patents, follow a similar pattern. We find that on-the-job training expenditures are countercyclical and, unlike R&D investment, credit constraints seem not to affect their cyclical behaviour. Investments in other intangibles, such as patent purchases, are found to be acyclical, also irrespective of financial constraints, which could suggest some kind of substitution between R&D and patent purchases over the cycle. Finally, complementarities between the different intangible investments and the traditional productive factors (labour and capital) are also investigated via production function estimates, in order to assess potential indirect effects of the cycle on long-run growth.

**Keywords:** R&D, business cycle, credit constraints, panel data.

**JEL Classification:** O3, E32, D22, C23.

**Resumen**

Este trabajo contrasta la teoría del coste de oportunidad utilizando un panel de empresas españolas para el período 1991-2010. Según esta teoría, las actividades que mejoran la productividad empresarial, como por ejemplo la inversión en I+D, deberían aumentar durante la fase baja del ciclo, ya que su coste relativo en términos del producto final que se deja de producir cae. Este hecho podría implicar que los ciclos económicos pueden tener un impacto (positivo) sobre el crecimiento de la productividad a largo plazo. En línea con la importante contribución de Aghion et al. (2007), realizamos un ejercicio empírico en el que permitimos que el efecto del ciclo económico sobre el gasto en I+D varíe entre empresas con distinta capacidad de acceder a la financiación externa, y encontramos que las restricciones crediticias pueden llegar a revertir la contraciclicidad de la I+D, aunque ello no sea lo óptimo para la empresa. En este trabajo se da un paso más y se explora si existen otras actividades beneficiosas para la productividad empresarial, como el gasto en formación o la adquisición del derecho de uso de patentes, que siguen un patrón cíclico similar al de la I+D. Los resultados apuntan a que el gasto en formación de las empresas es contracíclico y, a diferencia de la inversión en I+D, dicho patrón no parece verse afectado por la presencia de restricciones financieras. La inversión en otros activos intangibles, como las compras de patentes, resulta ser acíclica, también con independencia de las restricciones de crédito, lo que podría sugerir cierto grado de sustituibilidad entre la inversión en I+D y las compras de patentes a lo largo del ciclo económico. Finalmente, también se estudian las complementariedades entre los diferentes tipos de inversión en activos intangibles y los factores productivos tradicionales (trabajo y capital físico) mediante la estimación de una función de producción translog, con el objeto de valorar la existencia de potenciales efectos indirectos del ciclo económico sobre el crecimiento a largo plazo a través de la acumulación del factor trabajo y el capital físico.

**Palabras claves:** I+D, ciclo real, restricciones de crédito, datos de panel.

**Códigos JEL:** O3, E32, D22, C23.

# 1 Introduction

Since the 1990s a lot of theoretical and empirical papers have attempted to shed some light on how business cycles affect long-term productivity growth. The learning-by-doing theory, for example, claims that people have ideas on how to improve production efficiency precisely when they are producing, a process that is more intense during economic booms. Hence, economic booms (recessions) would have positive (negative) long-term effects on productivity. There are other theories, however, that claim that recessions could have a positive effect on long-term growth. One of them is the creative destruction theory, based on the original work of Schumpeter in the 1930s, and revived by Caballero and Hammour (1994). The theory states that recessions are times at which factors of production shift from (old) less productive units to more productive (new) ones, which, in turn, has a positive effect on aggregate productivity.

Reorganisation can also take place at the firm level. In this respect the opportunity-cost theory claims that limited resources within the firm can be devoted to production or to productivity-enhancing activities (PEA), such as the reorganisation of production, on-the-job training or research and development. These activities detract resources from current production i.e. they are costly in terms of forgone production, and their benefit extends into the future. Given the fall in revenue from normal productive activities during recessions, the opportunity costs of such activities will be at their lowest in times of crisis. Hence, the opportunity-cost theory claims that it will be optimal for firms to devote more of their limited resources to PEA during recessions, the result of which could be an increase in long-term productivity growth.[1]

Most of the empirical tests of this theory concentrate on R&D spending, one of the most important PEA. R&D activities are labour and finance intensive and, therefore, as stated by the opportunity-cost approach, can (add) detract labour resources from other productive activities during the (expansionary) contractionary phase of the business cycle.[2] The forgone cost in terms of output of such activities would fall during recessions and, therefore, we would expect firms to devote more resources to R&D in such troubled times. In other words, R&D is expected to be countercyclical.

There are many papers studying the cyclical properties of R&D expenditures – and other PEA – both at the micro and macro level. As regards the latter, the first vintage of papers – see footnote 1 – analysed the effect of cycles on aggregate TFP growth, understood as the result of some unspecified PEA, and tended to find broad support for the opportunity-cost approach.[3] However, the most recent empirical literature, which

**1.** The opportunity-cost theory developed from contributions by Bean (1990), Hall (1991), Aghion and Saint-Paul (1998), Davis and Haltiwanger (1992) and Galí and Hammour (1993).

**2.** See Saint-Paul (1997) for a discussion of the conditions under which a trade-off between production and PEA may exist, and in particular, its relationship with the theory of labour hoarding. As a matter of fact, many of the employees involved in R&D are not scientists, but support staff who could be employed in other parts of the production process. According to statistics from Eurostat, the share of researchers in total personnel devoted to R&D activities in the Spanish business sector is about 44.4 %, the share of technicians is 37.7 % and the share of support staff is 17.9 %. This notwithstanding, as far as we know, there are no papers documenting the fact that R&D personnel are shifted from research activities to production activities during booms, and vice versa. This could be an avenue that deserves future research.

**3.** These papers usually used a semi-structural VAR approach due to the endogenous nature of both economic cycles and productivity, in the spirit of Blanchard and Quah (1989). Estrada and Montero (2009) find evidence that private R&D is countercyclical in Spain using a SVAR approach in which the endogenous variables are real GDP, the GDP deflator, business sector R&D and public sector R&D.

usually adopts a single-equation framework, typically finds a procyclical relationship between R&D spending and aggregate output (see Geroski and Walters, 1995; Rafferty, 2003; Wälde and Woitek, 2004; and Comin and Gertler, 2006 for a sample of representative papers and the references therein).

As for the microeconomic literature, which is the relevant branch for our paper, there are a number of papers that study the cyclicality of R&D with conflicting results. One of the most prominent is Barlevy (2007), who constructs and calibrates a model where R&D expenditures are procyclical due to the presence of dynamic spillovers. Those spillovers result in limited appropriability of new products, which means that there is only a short window of time to appropriate profits from innovation. Hence, firms will introduce new products when they can extract the highest benefits, that is, when market conditions are optimal (i.e. booming).

On the other hand, recent major contributions by Aghion and co-authors (2007, 2010) explain this apparent contradiction between the empirical evidence and what we would expect from the opportunity-cost theory through the existence of credit constraints.[4] If a firm depends on external resources to perform R&D activities, when the bad times come its ability to borrow in order to innovate will be reduced, given the drop in current earnings. The consequence is that a negative shock should affect more R&D investments and innovation in firms that are more credit constrained. They test this possibility using a panel of French firms for the period 1993-2004, and find that in the absence of credit constraints, the share of investment in R&D at the firm level moves countercyclically, as expected by the opportunity-cost theory. However, when one allows that effect to vary between firms which are financially constrained and those which are not, the result changes: the R&D investment share turns procyclical in firms that are more dependent on external sources for financing innovation. This same result is also found, using the CIS database, by Bovha-Padilla *et al.* (2009) for Slovenian firms.

The aim of this paper is to contribute to the microeconomic literature on testing the opportunity-cost approach extended with the presence of liquidity constraints by expanding the analysis in several directions. In the spirit of Aghion *et al.* (2007), we study how the existence of credit constraints affects the cyclicality of R&D expenditures of Spanish firms during the period 1991-2010, a broader period than that considered in Aghion *et al.* (2007), which allows us to include the 1991-1993 crisis and, above all, the first three years of the current financial crisis.

Secondly, and given the previous discussion, we study whether other PEA follow a cyclical pattern in line with what one would expect according to the opportunity-cost theory. To this end, we expand our analysis to explore the cyclicality of training spending or patent purchases. As regards on-the-job training, in recessions it may be optimal for firms to devote some of the working time of their hoarded labour to build up human capital rather than to produce, given the lower opportunity cost of the former. As to the purchase of patents, most of the empirical work focuses on in-house R&D activity, but firms can also buy the right to use and exploit the results of others' R&D activity. The inclusion of such source of innovative

**4.** Another relevant explanation of the observed procyclicallity of R&D is offered in Ouyang (2011). She argues that there is an aggregation bias in the studies of the cyclical behavior of aggregate R&D. If aggregate R&D is dominated by the movements of a certain industry which is not synchronised with aggregate fluctuations, we could see that in aggregate terms R&D is procyclical but, at the level of the industry, R&D is moving countercyclically, as suggested by the opportunity-cost theory. Further, using industry-level data for the US she finds evidence consistent with the hypothesis of the existence of financial constraints, since the response of R&D to output is negative for positive demand shocks, but negative for a contractionary demand shock, due to decreases in firms' net worth and therefore tighter liquidity constraints.

activity at the firm level is of interest given the lower cost of patent purchases, relative to in-house R&D activity, and therefore, the possibility to substitute one for the other in times of financial difficulties.[5, 6]

The results of our analysis are consistent with those in Aghion *et al.* (2007): in the absence of credit constraints, firm-level R&D activity is countercyclical, that is, the opportunity-cost theory is confirmed. However, if we allow the effect of the cycle to vary depending on the probability of facing financial obstacles, we find that this result only holds for those firms with lower credit constraints.

Moreover, as regards other PEA, in the case of on-the-job training, it follows the same countercyclical pattern as R&D, but credit constraints are of no relevance in this respect. Lastly, investment in other intangibles, such as the purchase of patents, is much less sensitive to the cycle than R&D activity (or on-the-job training). This suggests the possibility that firms substitute one type of investment in intangibles for others in bad times.

Thirdly, and given the novelty of this last finding, we devote a whole section of the paper to the potential existence of indirect effects of business cycles on long-run growth stemming from the pattern of complementarities and substitutabilities among the different productive factors. We find that R&D capital and labour are complements, whereas R&D capital and physical capital are substitutes in the production function. Finally, we find mild evidence of substitutability between in-house R&D capital and intangible capital not produced within the firm (linked to knowledge accumulated through the purchase of patents).

Additionally, another novelty of our paper relates to the construction of the proxy for credit constraints, which implies matching two databases. The main source of information is the "Central de Balances" (CBSO – Central Balance Sheet Data Office) of the Banco de España. This database contains detailed balance sheet information on investments in tangible and intangible assets, financial situation, characteristics of the labour force and other variables of interest, such as spending on R&D and training, for a sample of over 3,200 Spanish firms during the period 1991-2010. However, as it has long been established in the literature, balance sheet based indices of financial constraints, like cash-flow measures, might present some limitations (Kaplan and Zingales, 1997; Whited and Wu, 2006). Given the importance for our analysis of correctly measuring financial constraints, we have used survey data which, combined with the balance sheet data, has enabled us to construct a reliable indicator of innovation-related financing obstacles for all firms in the CBSO sample. More concretely, we use the specific answers about obstacles to innovation reported to the Spanish Technological Innovation Panel (PITEC) to estimate the probability of being financially constrained for firms in the CBSO database.

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**5.** The percentage of firms claiming to invest in other intangibles such as the purchase of patents or licenses is about 30% in our sample, hence it is not negligible. It is true, however, that the amount invested is small, about 0.04% of total investment in p75 (5% on average). Lastly, the average size of firms investing in these types of intangibles is very large, and they have around 1,200, employees compared with firms with 800 employees which invest in training.

**6.** Some authors have also focused their attention on non-R&D PEAs. Nickell et al. (1995) used survey data to explore, for a very limited sample of UK firms, the causality between profit growth and the introduction of managerial reorganisation and new technologies. They find that worsening performance tends to be followed by an increase in the probability of the firm introducing new technology as well as other managerial and organisational changes. However, higher financial pressure only decreases the likelihood of introducing new technology, while it has no significant impact on other changes in organisation or human resource practices. Geroski and Gregg (1995) consider the effect of recessions on other intangible investments, such as training and marketing spending. They find that these expenditures are more sensitive to cyclical pressures than investments in implementing product or process innovations, but less sensitive than investment in plant and equipment. This notwithstanding, their analysis is unconditional and does not consider specific firms' characteristics that might distort those investment choices, such as the degree of credit constraints.

The remainder of the paper is structured as follows. Section 2 describes the two datasets we combine to perform the analysis and details the construction of the direct indicator of financial obstacles. Section 3 studies the cyclicality of R&D expenditures using several measures of firms' R&D activities and section 4 expands the analysis to include investment in other intangibles. Section 5 studies in more depth the substitution/complementarity of the different factors of production, putting special emphasis on the relationships between the different investments in intangibles and, finally, section 6 presents the conclusions.

## 2 Data and issues in measuring financial constraints

### *2.1 The Banco de España's CBSO*

In this paper we use firm-level information from the Banco de España's CBSO. Since 1983, the CBSO has been compiling and publishing aggregate information of reporting firms' balance sheets in order to follow the economic situation of the Spanish private non-financial sector. The information is provided on a voluntary basis every year by a substantial number of established companies, which amounted to 9,000 non-financial firms in 2007 ("reporting firms").[7] The reporting firms fill in a questionnaire with detailed accounting information, as well as some other additional information on employment, breakdown of the workforce in terms of skills, type of contracts, spending on training 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 omissions. Moreover, about 75% of the firms are contacted again to clarify certain data 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, the energy sector is very well covered, with a value-added coverage rate of over 70%. Industry and market services – especially trade, postal services, transport and telecommunications – are quite well covered: reporting firms account for about 30% of value added and about 20% of total employment in industry, while the respective figures in the market service sector are 20% and around 23%. On the other hand, agriculture, mineral extraction and construction have a coverage rate of less than 10%, both in terms of value added and employment.[8] Another important source of bias is the larger-than-average size of reporting firms. In the industry sector, for example, about 50% of firms in the sample had less than 250 employees, compared with more than 95% in the population. Therefore one has to be cautious when extrapolating the results of our analysis.

After editing the data,[9] we selected those firms with at least three consecutive years of information. The result is an unbalanced panel covering the period 1991-2010[10] which contains information for 3,278 firms (26,543 observations in total). Table 1 shows the basic characteristics of the CBSO database.[11]

### *2.2 The Technological Innovation Panel (PITEC)*

As stated in the introduction, a key part of our analysis is based on the fact that some firms might face credit constraints in financial markets, above all at times of distress. If that were the case, even if those firms found it optimal to increase investment in PEA during recessions due to its lower opportunity costs, they might not be able to do so because they have no

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**7.** The self-employed are not included. In 2007, about 50% of the reporting firms were corporations and 45% were limited liability companies. The rest were mainly cooperatives.

**8.** Firms are classified under the different economic sectors according to their main activity.

**9.** We drop observations with a negative value of capital stock and value added, as well as those with excessive changes in employment or investment. We also drop firms operating in the non-market economy, and those having experienced any type of restructuring, such as mergers and acquisitions. Lastly, we identify outliers (above or below p 99 and p 1, respectively) and substitute their value by the corresponding threshold.

**10.** The coverage of 2010, the last year of the database, is only partial with about 900 observations compared with 1,300 or more observations for the other years.

**11.** For more information on this database, please see López-García and Montero (2010).

access to the required external funds. One of the novelties of this paper is that we are able to exploit survey information from the Technological Innovation Panel (PITEC). PITEC is a longitudinal database constructed on the basis of the annual Spanish responses to the Community Innovation Survey (CIS) and is managed by the Spanish National Institute of Statistics (INE).[12] The survey contains detailed information at the firm level on the inputs and outputs of the innovation process for a sample of about 10,000 Spanish firms. Although the panel started in 2003, we use it from 2004 to 2009 for reasons of comparability.[13]

Although access to the database is public and free for researchers, observations are anonymised to preserve confidentiality. We had access, however, under a strict confidentiality agreement, to the fiscal identification numbers of a sample of firms so we could merge the PITEC information with the balance sheet information from the CBSO database. The merger was positive for about one-fifth of the observations – around 600 matched observations per year – in the CBSO database between 2004 and 2009.

### *2.3 Constructing a proxy for financial obstacles to innovation*

The indicator of credit constraints is based on the direct answer provided by firms to the (very specific) PITEC question:

*"During the two previous years, how important was the lack of finance from sources outside your enterprise for hampering your innovation activities?"*

Firms have to rank the importance of this factor from 1 (high) to 3 (low).[14] The procedure for constructing a credit constraint indicator for all firms in the CBSO sample (that is, not only for the matched firms) is inspired by the work of Coluzzi *et al.* (2008). It consists of two stages. In the first stage, we use an ordered probit model to estimate the relative importance of some firms' characteristics in explaining the existence of financing obstacles. We perform this exercise for firms who responded to the PITEC questionnaire and had a positive matching in the CBSO database (a total of 946 firms). The set of explanatory variables includes those suggested by the literature, such as age, size, debt ratio, collateral, sector of activity, etc. In the second stage, we use the estimated coefficients of the first-stage preferred specification to compute, according to the value of the corresponding explanatory variables, the predicted probability of facing financial obstacles (that is, of responding that the importance of financial constraints for hampering innovation is high) of all firms in the CBSO database.

Table 2 shows the percentage of those claiming to be financially constrained (in respect of carrying out innovative projects) according to size, age, sector of activity and some financial ratios.[15]

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**12.** PITEC is sponsored by Fundación Española para la Ciencia y la Tecnología (FECYT) and the COTEC Foundation and managed by the National Institute of Statistics. It can be reached at the following link: http://icono.fecyt.es/contenido.asp?dir=05)Publi/AA)panel

**13.** In 2003 the sample contained about 73% of firms with 200 or more employees and a sample of firms undertaking internal R&D expenditures in 2003. In 2004 the sample was enlarged to include firms with less than 200 employees and with external R&D activities, and a representative sample of small non-innovative firms (with less than 200 employees).

**14.** There is a fourth possibility: "does not apply". We decided that firms that responded "does not apply" and had positive R&D expenditure were not constrained, whereas those that gave the same response but did not perform R&D were not considered.

**15.** We consider that a firm is financially constrained in Table 2 if it reports a lack of external finance as an important factor hampering innovation. If, on the other hand, the firm responds that the lack of finance is of medium or low importance, we consider it not to be financially constrained. The reason for this distinction is the fact that financial pressure has been proven to have a highly non-linear impact on business activity by the literature, and that it only becomes relevant when financial pressure exceeds a certain threshold (see, for example, Hernando and Martinez-Carrascal 2003).

On average, 23% of firms think that the lack of external funds is seriously hampering their innovative activities (hence, they are financially constrained). If we draw a distinction by sector of activity, the highest proportion of constrained firms is found in the construction sector, and the lowest in manufacturing. Small firms (less than 50 employees) and very young firms (less than 10 years old) also seem to be more financially constrained. Lastly, firms with a very low share of tangible assets (than can be collateralised), limited cash flow and those with high debt ratios and total debt burden seem to suffer as well from higher financing obstacles.

These descriptive results confirm what we would expect from the literature on financial constraints, largely based on the seminal paper of Fazzari *et al.* (1988). The determinants of firms' financial constraints identified by this literature are linked, in the first place, to the degree of opacity of the company from the point of view of the lender and include, most importantly, size and age (see, for example, Gilchrist and Himmelberg, 1991 and Coluzzi *et al.,* 2008). There is a second group of determinants related to the financial vulnerability of the firm, such as the quantity and quality of collateral, debt ratio or financial burden (see, for example, Bernanke *et al.*, 1996; Hernando and Martinez-Carrascal, 2003; and Atanasova and Wilson, 2004). Lastly, there are a number of papers that stress that variables related to access to alternative sources of finance, such as being quoted in the stock market or belonging to a group, are also important (Harrison and McMillan, 2003).

In the first stage of the analysis we rely on the PITEC survey data to analyse which of the firm's characteristics suggested by the literature make it more likely for it to be financially constrained when it comes to investing in innovation. For that purpose, we assume that the firms' underlying response can be described by the following specification:

$$D^*_{i,t} = x_{i,t}\beta + \delta\Delta y_t + \mu_j + \varepsilon_{i,t} \tag{1}$$

$$\left.\begin{aligned} D_{i,t} &= 1 \; if \; D^*_{i,t} \leq c_1 \\ D_{i,t} &= 2 \; if \; c_1 < D^*_{i,t} \leq c_2 \\ D_{i,t} &= 3 \; if \; D^*_{i,t} > c_2 \end{aligned}\right\} \tag{2}$$

where $D_{i,t}$ is the answer (on a scale from 1 to 3) reported by firm *i* at time *t* to PITEC's question on financing obstacles, $D^*_{i,t}$ represents a latent variable modeling the responses, $x_{i,t}$ is a vector of firms' characteristics, and $\beta, \delta, c_2, c_1$ refer to parameters and thresholds to be estimated. We include as well the growth rate of aggregate GDP ($\Delta y_t$) to capture aggregate developments which could have an impact on the probability of firms accessing external finance and we control for industry-specific effects including a set of sector dummies ($\mu_j$).[16] Standard errors will be consistent as long as the regression residuals are uncorrelated across both firms and years; since such uncorrelatedness is unlikely to hold in our case, we cluster the estimated standard errors.

Given that the dependent variable is categorical and can take on 3 values, we use a pooled ordered probit model to estimate the model in (1) and (2). We have also tried, however, a probit model where the dependent variable takes the value of 1, if the firm responds that the lack of finance is important and 0 if it is not.[17] As suggested by the

**16.** We include dummies for manufacturing, construction and services and dummies for 10 more disaggregated sectors of activity: extraction, manufacturing, utilities, retail, hotels and restaurants, transport, postal services and telecommunications, real estate activities and other market services.

**17.** We have also tried exploiting the panel structure of the PITEC database and run a random effects probit model with very similar results.

literature, we have included among the explanatory variables the firm's age and size[18] as well as a dummy if the firm is quoted in the stock market (=1 if quoted). We have also included four variables related to a firm's financial vulnerability, all lagged one period: (1) the leverage ratio, defined as the ratio of interest-bearing external funds to internal funds; (2) cash-flow divided by the stock of capital at the beginning of the period; (3) total debt burden defined as the ratio of the cost of external funding to cash-flow; and (4) collateral, defined as the share of tangible assets over in total assets.[19]

Table 3 reports the marginal effects from the estimation of the first-stage regressions. Columns [1] to [3] show the results with different measures of age and size, 3 broad sectors of activity and the lagged debt ratio, total debt burden, cash-flow and collateral.[20] Column [4] shows the results with 10 sectors of activity and column [5], our preferred specification, keeps only the significant variables.[21] Lastly, column [6] repeats the analysis using a pooled probit model. Results are fairly robust and in accordance with what we could a priori expect from theory. Older firms have a lower probability of facing financial obstacles when it comes to innovation, while being small increases that probability by 14 pp. That very large impact of size is very similar to the one found in Coluzzi *et al.* (2008), in spite of the different databases used. Manufacturing and services firms have significantly less probabilities of facing credit constraints compared to firms operating in the construction sector and, among the variables reflecting the financial position of the firm, only the firm's collateral turns out consistently not to be important.

The next step is to use the estimated coefficients to impute a probability of facing credit constraints to innovation to all firms in our CBSO sample. All tables in the following sections present the results using the probability of facing financial obstacles estimated from the coefficients of column [5]. To check the robustness of the results, however, we have redone all the tables with the coefficients estimated using the alternative probit model.[22]

The last row of Table 3 shows the percentage of firms that claimed to be financially constrained in PITEC and have been correctly imputed as such according to the estimated probabilities and, conversely, those that claimed not to be constrained and were predicted correctly. That percentage of correctly classified firms is above 70% in all cases.

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**18.** We have tried different specifications. With respect to age, we have tried the log of the firm's age as well as a dummy that takes the value one if the firm is less than 10 years old and zero if it is not. With respect to size we have included the log of the number of employees and a dummy for small firms (less than 50 employees).

**19.** We have also explored alternative specifications in this respect. Apart from including the lagged value of the financial ratios we have also tried with the deviation of the firm's ratio with respect to the sector's average that year and with a dummy that takes the value one if the firm's ratio is above the sector's median for that year. For a detailed definition of the variables please refer to the Appendix.

**20.** After many tries we found that the effect of a firm's cash-flow was not linear. It made a significant difference on the probability of being credit constrained only when entered as a dummy taking the value one if the firm's cash-flow is above the sector's median.

**21.** Note that the aggregate variable is not significant in any of the ordered probits. We tried with alternative variables such as the interest rates charged by banks to firms but it also turned out to be non-significant.

**22.** Results did not change. In any case, they are available upon request.

## 3 The cyclicality of the R&D share and credit constraints

### *3.1 Baseline specification*

In this section we estimate the cyclicality patterns of R&D investment across the Spanish firms in our sample, and how these patterns might differ in those firms that are more credit constrained. In particular, we conjecture that R&D investment should be more procyclical in firms facing tighter credit constraints. The rationale for this hypothesis is based on Aghion *et al*. (2010) who put forward a model in which firms can choose between short-run capital investment and long-term R&D investment. Moreover, innovation requires that firms survive short-run liquidity shocks which might be absorbed by the firms relying on either short-run earnings or borrowing. Whenever the firm is hit by a bad shock, its current earnings are reduced and, therefore, so is the firm's ability to borrow in order to innovate. This implies that a negative shock should hit R&D investment more in firms that are more credit constrained.

On the other hand, our main interest is on how R&D investment decisions are affected by cyclical shocks and credit constraints in relative terms to other capital investment decisions. For instance, a firm hit by a negative shock might reduce both R&D and physical capital investment; however, as long as the reduction in physical capital in larger in absolute terms than the reduction in R&D investment, the share of R&D over total investment would increase providing evidence in favor of the opportunity cost theory. Hence we focus on the share of R&D investment over total investment as our variable of interest.

All in all, in order to test the theoretical predictions just described, we follow Aghion et al. (2007) and estimate the following equation:

$$\frac{RD_{it}}{RD_{it}+I_{it}} = \beta_0 + \sum_{h=0}^{2} \beta_{h+1}\Delta s_{it-h} + \gamma_0 CC_{it-1} + \sum_{h=0}^{2} \gamma_{h+1}\Delta s_{it-h} CC_{it-1} + \mu_j + \eta_i + u_{it} \tag{3}$$

where $RD_{it}$ represents R&D investment, $I_{it}$ physical investment, $CC_{it-1}$ the probability that firms are credit constrained, and $\Delta s_{it}$ the (log) variation in firms' real sales. We also account for industry dummies ($\mu_j$) and firms' fixed effects ($\eta_i$), while $u_{it}$ represents the usual error term.[23]

$CC_{it-1}$ is estimated as explained in Section 2, while the other variables come from the CBSO database. $RD_{it}$ is proxied by R&D expenditures; whereas $I_{it}$ is approximated by gross fixed physical capital formation and $s_{it}$ is the firm's real sales, deflated with the value added deflator at a sectoral level (see Table A1 in the Appendix for a description of all the variables).

As explained above, we expect the share of R&D investment to be countercyclical in the absence of credit constraints, in line with the opportunity-cost approach, which implies that $\beta_1<0$ and $\Sigma_i\beta_i<0$ (i=1,2,3). However, since financial constraints are supposed to reverse the cyclicality of investment composition, they should lead to a more procyclical R&D share, i.e., $\gamma_1>0$ and $\Sigma_i\gamma_i>0$ (i=1,2,3).

**23.** We include 25 sector dummies, see Appendix. In any case, results without sector dummies are virtually the same since their effects should already be captured by the firm dummies.

Finally, we do not expect a particular sign for $\gamma_0$. On the one hand, a firm may reduce its demand for short-run productive investment when it is financially constrained (as shown, for instance, by Benito and Hernando, 2002, for the case of Spanish firms); however, long-run productivity-enhancing investments should also be affected negatively by credit supply (as shown by, inter alia, Hall's (2002) survey, and López-García and Montero (2010) for Spanish firms). Thus, depending on the relative strength of these two effects, $\gamma_0$ may be either positive or negative.

As regards the estimation method, we first consider the Within Groups (WG) estimator given that we find it appealing to allow correlation of the unobserved firm heterogeneity ($\eta_i$) with the independent variables. Second, in order to alleviate potential simultaneity biases arising from the joint determination of sales and both types of investment, we use an instrumental variables approach, the first-differenced GMM estimator discussed in Arellano and Bond (1991). This technique is based on taking first differences of the variables to eliminate the time-invariant effects and then on using lagged levels of the regressors as instruments for their first-differences. In particular, we assume that both sales and credit constraints are predetermined with respect to the R&D investment share so that instruments lagged t-1 and earlier are assumed (and tested) to be valid. The use of "internal instruments" makes this approach particularly attractive in our setting, where it is difficult to find appropriate external instrumental variables. Finally, note that the predeterminedness assumption made for estimation implies that current shocks to investment decisions made by the firm do have an effect of future sales and credit constraints which seems sensible at the frequency of yearly data considered here.

Table 4 reports the results from estimating equation (3), both using the GMM and WG estimators. The first results that are worth highlighting show that the share of R&D investment is indeed countercyclical. The coefficient estimates for the variation in current sales are negative and statistically significant at conventional levels, which is robust to the use of the GMM estimator and to the inclusion of additional regressors. The coefficients for the first and second lags of the change in sales are also correctly signed and have a statistical significance robust to the estimation method. As regards the economic relevance, a 10% change in current sales would induce a reduction in the share of R&D of between 0.1 percentage points (pp) and 0.8 pp that same year. Moreover, if we take into account the results under column [9], that effect would be quite persistent and in the order of 1.9 pp accumulated by t-2. This magnitude is quite important, since it implies a 26% cut in the average R&D share.[24]

When we introduce $CC_{it-1}$ as an additional regressor, the countercyclicality of the share of R&D does not change (columns [4]-[9]). This variable alone shows no significant impact on the R&D share in any of the specifications. This would provide some evidence that R&D spending tends to be affected as much by credit constraints as by physical investment. However, when $CC_{it-1}$ is interacted with the sales shock variables, we obtained results consistent with the theoretical predictions (positive and statistically significant coefficients) i.e. the share of R&D turns less countercyclical in the presence of financial constraints, a result that is robust for all the variation in sales considered (in t, t-1 and t-2). Indeed, for those firms

**24.** It should be noted that the distribution of the R&D share is highly skewed (the median share and the 75% percentile are 0%). If we were to take as a reference the 80% percentile, the reduction in the R&D share would amount to close to 83%.

where $CC_{it-1} \rightarrow 1$, the sensitivity to real sales growth would be $\Sigma_i\beta_i+\Sigma_i\gamma_i > 0$, in other words, the R&D share would be procyclical.[25]

### 3.2 Robustness checks

In order to check the robustness of our results, we have carried out a set of additional empirical exercises, a selection of which is presented below. First, we have studied whether using an alternative definition of the R&D share changes the results. Second, we comment on some other empirical exercises that we do not report. And thirdly, we check whether the countercyclicality of the R&D share is determined by the behaviour of the level of physical investment.

Table 5 reports the results from estimating equation (3) using different normalisations of R&D spending. To be more specific, we have used as dependent variables the ratio of R&D expenditures to i) gross value added (GVA); ii) total employees (in real terms); iii) gross operating surplus (GOS); and iv) the ratio of R&D employees to total employees. In one way or another, all these ratios reflect a trade-off between a PEA and a productive activity. The ratio to GVA would account for the trade-off between producing today (i.e. generating value added today) and improving production tomorrow (through PEAs such as R&D). The ratio of R&D to GOS would change the focus to profitability: either you generate profits today, or you invest to enhance your profits tomorrow. Finally, the ratio of R&D employees to total employment is a real measure proxying for how labour resources are distributed within the firm.

As Table 5 shows, all these dependent variables convey the same message, that is, no matter how you measure the R&D share it turns out to be countercyclical, since the coefficient of the variation of sales is negative and tends to be statistically significant across specifications. Moreover, the share of R&D investment becomes less countercyclical in the presence of credit constraints, as the parameter for the interaction term ($\Delta s_{it} \cdot CC_{it-1}$) is positive and significant.

Additionally, we have checked the robustness of these results to the definition of the variable proxying for the cycle. To this end, we have substituted firms' sales by firms' GVA and output (both measured at basic prices and deflated with the sectoral value added deflator). Results in Table 4 turned out to be qualitatively similar. Moreover, we have used other measures of credit constraints derived from the same framework described in Section 2 (using results from columns [1]-[4] and [6] in Table 3). Again, results in Table 4 would be qualitatively similar.[26]

Finally, as the denominator of the R&D share (i.e. R&D spending + physical investment) is not constant over the firm's business cycle, our baseline results do not provide direct information on how the average *level* of R&D investment is affected by both the cycle and credit constraints. For instance, a countercyclical R&D share would be consistent with the level of R&D either decreasing or increasing, if it turned out that the level of physical investment decreases sufficiently during slumps.

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**25.** The p-value for the test of the null hypothesis that $\Sigma i\beta i+\Sigma i\gamma i > 0$ in column [6] is 0.14, so we cannot reject that for those firms with $CCit\text{-}1 \rightarrow 1$ the R&D share is procyclical.

**26.** For the sake of brevity, we do not report these results, but they are available upon request. We have also estimated a specification for only the firms included in PITEC and using as a proxy for credit constraints the direct answer to the question of lack of external finance, but, unfortunately, estimation results were less robust than in our baseline specification. Although we tended to find that the coefficient on sales growth was negative and statistically significant, the interaction of sales with the direct measure of financial obstacles was sometimes positive and other negative, and rarely significant. These results are also available upon request.

One way to solve this ambiguity is to estimate the following specification for the *level* of physical investment:

$$\frac{I_{it}}{K_{it-1}} = \alpha_0 + \alpha_1 \frac{I_{t-1}}{K_{t-2}} + \sum_{h=0}^{1} \beta_{h+1} \Delta s_{it-h} + \gamma_0 CC_{it-1} + \sum_{h=0}^{1} \gamma_{h+1} \Delta s_{it-h} CC_{it-1} + \mu_j + \eta_i + u_{it} \tag{4}$$

where $I_{it}$ is physical investment, $K_{it-1}$ denotes the stock of physical capital and the other variables are defined as in equation (3). This equation would be similar in spirit to those that test for the presence of financial constraints.[27] In line with this literature, we expect physical investment to be procyclical ($\beta_1,\beta_2>0$) and negatively affected by credit constraints ($\gamma_0<0$), while the interaction of such constraints with the sales shocks should be positive ($\gamma_1,\gamma_2>0$), as financial constraints – procyclical per se – should strengthen the procyclicallity of physical investment. Again, we estimate this equation with the WG and GMM estimators.

Table 6 shows the results from estimating equation (4). As can be seen, physical investment turns out to be procyclical, with both parameters on the variation of sales being positive and highly statistically significant (see columns [1], [2], [4] and [5]). However, when we introduce our proxy for financial constraints, that significance is lost. Moreover, and contrary to previous literature, the proxy for credit constraints is not statistically significant, either alone or when interacted with the variation in sales.[28] This could be the result of the way the indicator of credit constraints has been built, given it is based on firms' responses about obstacles to innovation.[29] Yet, since we want to show that the results in Table 4 concerning the interactions $\Delta s_{it-k} \cdot CC_{it-1}$ (k=0,1,2) are not driven by the dynamics of physical investment, we must stick to this indicator in order to be consistent.

In sum, our results point to a countercyclical share of R&D and a procyclical *level* of physical investment. What does this imply for the behaviour of the level of R&D expenditures? Let us assume that we are in a recession; therefore, the countercyclicality of the R&D share means that this ratio would be increasing. However, given that the level of physical investment is procyclical, this would be consistent with R&D either increasing or decreasing (although to a lesser extent than physical investment). Regression results reported in Table 5 show that indeed the *level* of R&D investment – normalised using several denominators, such as the GVA, the GOS or R&D employees – would be countercyclical. Thus, our results suggest that when Spanish firms are facing a downturn, they tend to adjust productive investments and to either preserve or increase R&D, which would be consistent with the view espoused by the opportunity-cost approach.

### *3.3 Heterogeneous effects*

In a recent paper, Cincera *et al.* (2011) investigate the adjustments in corporate R&D and innovation strategies during the current economic crisis. More specifically, the paper provides evidence that adjustments in R&D investments are less pronounced in firms with higher levels of R&D intensity. This raises the question whether our findings also hold for different types of firms regarding R&D intensity levels. Cincera *et al.* (2011) also explore the effects of firms' age on their R&D investment decisions. They find that R&D

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**27.** See the pioneering work of Fazzari et al. (1988) and the subsequent literature that developed afterwards.

**28.** This result also holds when we do not include the lag of physical investment –which is not per se significant.

**29.** Indeed, in Aghion et al. (2007) their proxy for credit constraints – based on the firms' credit history – turns out to be negative and significant, while the interactions are not, which means that physical investment is negatively affected by financial constraints irrespective of the firm’s position in the business cycle.

adjustments do not seem to depend on firms' age. We investigate this issue further by considering heterogeneous effects for high-growth firms. According to common definitions in the literature, high-growth firms are typically young firms succeeding at the beginning of their activity. Thus, our conjecture is that firms' performance as they take their first steps might be relevant for their R&D investments as opposed to firms' age as discussed in Cincera *et al.* (2011).

As suggested by the opportunity-cost theory, the hypothesis we maintain throughout the paper is that R&D investment as a share of total investment is countercyclical. However, we argue and provide evidence that this share of R&D investment might become pro-cyclical at sufficiently high levels of credit constraints. In this section we investigate the existence of heterogeneous effects regarding the cyclicality of R&D investment decisions and the role of credit constraints in such decisions. More concretely we consider three different types of firms for which this behaviour might differ, namely, high-technology firms, new innovative firms, and high-growth firms.

We classify as high-technology firms those companies belonging to the high-tech sector according to the Spanish National Classification of Economic Activities (CNAE 93). On the other hand, new innovative firms are those with zero R&D investment during the previous year and positive R&D in the current one. Finally, we label as high-growth firms those with more than ten workers and with over 20% growth for two or more consecutive years in the number of workers.

Our econometric test of the existence of heterogeneous effects is based on the inclusion of interaction terms in our baseline specification in equation (3). We first construct three dummy variables, one for each category of firm (i.e. high-technology, new innovative, high-growth). Then we interact each dummy with the change in sales ($\Delta Sales_t \times D_t$), and with the interaction of change in sales and our proxy for credit constraints ($\Delta Sales_t \times CC_{t-1} \times D_t$). If the first interaction ($\Delta Sales_t \times D_t$) is significantly different from zero, the cyclicality of R&D investments differs across different types of firms. If the second interaction term ($\Delta Sales_t \times CC_{t-1} \times D_t$) emerges as being statistically significant, we can conclude that credit constraints exert a different effect on the investment decisions of R&D investments across the firm categories we consider.

Table 7 presents the results including the interaction terms in our baseline specification. In particular, columns [1] and [2] refer to high-technology firms, in columns [3] and [4] we consider new innovative firms and columns [5] and [6] include the results of high-growth firms. In all three cases, there is no evidence of heterogeneous effects of credit constraints on R&D investment decisions. This is the case because the interaction term $\Delta Sales_t \times CC_{t-1} \times D_t$ is not statistically different from zero in columns [2], [4] and [6]. We thus conclude that previous R&D intensity and/or performance do not seem to affect the influence of credit constraints when firms determine the share of their investments earmarked for R&D activities.

In contrast, according to the estimates in column [1], R&D investments in high-technology firms are more countercyclical than in the other firms (the interaction coefficient is negative and significant). Since R&D is expected to be part of the core business in high-technology firms, it seems reasonable that these firms try to take more advantage of the lower opportunity cost of R&D during crises as suggested by the opportunity-cost theory. This result also holds for new innovative firms in column [3], which means that for those firms deciding to start their R&D activity, economic crises are more costly in terms of R&D. In contrast, firms with positive R&D investment in the previous period seem to have less pronounced adjustments in R&D in the downturn of the business cycle. This finding suggests that cyclical movements in R&D investment are more pronounced in the intensive margin rather than in the extensive margin. Finally, the cyclical behaviour of high-growth firms does not differ from the behaviour in other firms (the interaction is not significantly different from zero in column [5]).

## 4 Other intangible investment

At the firm level we have found that the share of R&D expenditures in total investment is countercyclical as suggested by the opportunity-cost theory, although only in the absence of "acute" credit constraints. In this section we estimate the cyclicality of other intangible / productivity-enhancing investments in order to test whether reallocation effects of recessions play any role beyond R&D. We also check whether the presence of credit constraints affects the cyclical behaviour of these other intangible assets.

Despite the prominent role of R&D in the group of productivity-enhancing investments, there are other components of the stock of intangible capital which could be important for long-term productivity growth. In particular, López-Garcia and Montero (2010) show that investment in human capital is a significant determinant of firms' innovative activity. Bean (1990) and Galí and Hammour (1993) author two of the few papers looking at the effect of cycles on human capital accumulation and find that, according to the opportunity-cost theory, firms might also shift resources to building human capital through job training of labour hoarded during recessions.

Following Aghion *et al.* (2007), the specification considered is the same as in the previous section. We first regress the variable of interest on a proxy for the business cycle at the firm level (change in sales) in order to estimate the raw cyclicality of the dependent variable. Then, we add an interaction of the cycle with our proxy for credit constraints faced by the firm in order to check the role of the latter on the cyclicality of the dependent variable.

Table 8a presents the results of estimating the cyclicality of training expenditures. In particular, we consider the ratio of training expenditures[30] to training expenditures plus total investment as the dependent variable to be consistent with the previous section. Overall, we find that, on the one hand, training expenditures are countercyclical, as expected from theory and, on the other hand, credit constraints do not seem to play any role in human capital formation within the firm.

More concretely, in columns [1], [2], [5] and [6] of Table 8a we estimate a negative and statistically significant effect from the cycle on training expenditures. This basically indicates that firms devote a larger share of their investment resources to human capital accumulation during recessions. This result confirms the findings in Galí and Hammour (1993) using a VAR approach at the aggregate level, and also provides evidence in favour of the opportunity-cost theory.

The magnitude of the estimated effects is also economically significant. In particular, a 10% decrease (increase) in current sales induces an increase (decrease) in the share of training expenditures in total investment of around 0.1 pp during the current period and of about 0.2 pp built up during the following year. This effect represents 6.3% of the average training expenditure share in our sample.

Columns [3], [4], [7] and [8] in Table 8a provide evidence that credit constraints do not seem to play any role in human capital investments for hoarded labour within the firm. In

**30.** As we have information on training spending from 1991 to 2007, we will use a shorter sample to carry out the analysis of that variable.

particular, we observe that neither the credit constraints proxy nor their interactions with the cycle are significantly different from zero. This result suggests that firms are able to shift resources to invest relatively more in on-the-job training during recessions. As suggested by Nickell *et al.* (1995), the rationale of this finding might be that investment in human capital is relatively more expensive in terms of time, but not in terms of money, so credit constraints are not a significant determinant of this type of investment.

All in all, these results seem to support the opportunity-cost theory: during recessions firms invest a relatively larger source of their resources in personnel training given the lower forgone cost of this PEA and, contrary to R&D investment, this process is not hampered by the presence of credit constraints.

Aside from R&D and training, there are other investments in intangibles which could enhance firms' productivity performance in the future. In 2000, the accounting rules changed in Spain and obliged firms to record under different balance sheet entries investment in R&D and IT applications[31] and other intangible investments "not produced" within the firm, which include mostly the purchase of the right to use and exploit external inventions i.e. patents purchase. This distinction, which can only be made for the period 2001-2010, between "in-house" R&D and purchase of external R&D might be of interest given that firms might buy patents when credit constraints prevent their own innovation activity, since the former are less expensive than the latter. This would indicate that firms facing liquidity problems might substitute their own R&D activity by purchasing innovation carried out by others (i.e. patent acquisition).

Table 8b reports the results from estimating our baseline equation distinguishing between investment in R&D and IT, on the one hand, and the purchase of patents, on the other. Columns [1] to [4] present the estimates from considering the ratio of investment in R&D and software applications to total investment. The results are consistent with those presented in Table 4, the ratio is countercyclical as expected, but becomes procyclical beyond a certain level of credit constraints. This reinforces the robustness of the results of Section 3, which were based on expenditures data instead of the narrow definition used here. Moreover, adding data on investments in software applications does not seem to change the cyclicality pattern of investment in R&D.

Columns [5]-[8] of Table 8b repeat the estimation of our baseline specification, but now considering the share of investment in patent rights in total investment as a dependent variable. The cyclical behaviour of these intangible investments is different from that of other intangibles, as it seems to be unrelated to the business cycle, i.e. acyclical. Despite the coefficients on sales being generally negative, they are not statistically significant in all cases. On the other hand, credit constraints do not play any role in this type of intangible investments, suggesting that firms decide the share of investment in patent acquisition regardless of sales volume and, in general, access to credit does not represent an obstacle for such investments. This distinct effect of the cycle on the decisions to invest in R&D or in patents could be uncovering some type of substitution between both types of investment at times of distress. Given the novelty of this finding, we take a closer look at the complementarity/substitutability of factors of production in the next section.

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**31.** Note here that the distinction between different intangible assets is only available with information on R&D investment rather than R&D spending as considered in previous sections. According to CBSO data, while R&D spending encompasses any kind of R&D-related expenditure, R&D investment only includes those expenditures devoted to R&D projects expected to somehow succeed in the future.

## 5 Complementarities between R&D capital and other factors of production

### *5.1 R&D capital versus physical capital and labour*

Although the overall benefits from R&D investment are widely accepted, how to efficiently promote such investment remains a challenge for policy makers. In previous sections we found some evidence in favour of the hypothesis that credit constraints are an important obstacle for R&D investment during downturns. An additional issue in this respect is the possible complementarities between R&D and the other factors of production, namely, physical capital and labour, and their potential indirect effects on aggregate productivity. The usual view that factors of production are substitutes is based on traditional mass production systems in which capital and unskilled labour are typically substitutes for each other; however, modern production technologies usually require that machinery, knowledge capital, and human capital are combined in a complementary fashion.

In the definition by Edgeworth,[32] two inputs are complements if an increase in the level of one input raises the marginal value of another input. That is, factors that are complementary tend to appear together: more of one factor is optimally accompanied by more of the other. This definition implies that if the relative price of R&D declines, firms will increase investment not only in R&D, but also in other complementary inputs. Therefore, if there are complementarities between R&D and labour, the aggregate cost of under-investment in R&D during downturns due to credit constraints might be exacerbated by an induced under-investment in labour, especially skilled labour, as an additional and complementary PEA. Thus, this would have an additional indirect effect on long-term growth, via less human capital accumulation.

In order to further investigate this issue, we estimate output and substitution elasticities based on a production function approach at the firm level. Briefly anticipating our findings, while some complementarities exist between R&D expenditures and labour, our empirical results seem to indicate that physical and R&D capital are substitute inputs. These findings lead us to the conclusion that the overall cost of R&D under-investment during downturns due to credit constraints might probably be exacerbated by a resulting under-investment in labour.

Despite the indisputable appeal of the popular Cobb-Douglas production function, it is not suitable for our purpose here since it constrains the substitution elasticities between different inputs to unity. Therefore, our methodological framework departs from a Translog production function (Christensen *et al.*, 1973) at the firm level as follows:

$$\ln\left(VA_{ijt}\right) = \alpha_K \ln K_{ijt} + \alpha_L \ln L_{ijt} + \alpha_C \ln C_{ijt} + \beta_{KK}\left(\ln \mathrm{K}_{ijt}\right)^2 + \beta_{LL}\left(\ln \mathrm{L}_{ijt}\right)^2 + \beta_{CC}\left(\ln \mathrm{C}_{ijt}\right)^2 + \beta_{KL} \ln K_{ijt} \ln L_{ijt} + \beta_{KC} \ln K_{ijt} \ln C_{ijt} + \beta_{CL} \ln C_{ijt} \ln L_{ijt} + \delta_t + \mu_j + v_{ijt} \tag{5}$$

where $VA_{ijt}$ refers to the Value Added in constant euro of firm $i$ belonging to sector $j$ in year $t$. $K_{ijt}$, $L_{ijt}$, and $C_{ijt}$ refer to the factors of production, physical capital, labour, and R&D capital respectively. On the other hand, $\delta_t$ and $\mu_j$ include a set of time and sector dummies respectively. While the time dummies aim to capture the common factors affecting all firms in

**32.** See Hicks (1970) for an overview.

a given year, the sector dummies control for systematic differences in production technologies across industries. Note that the Cobb-Douglas production function is a special case of the Translog where all the coefficients of the quadratic terms are set equal to zero.[33]

For production functions with more than two inputs, the most common measure of substitutability / complementarity is the Allen partial elasticity of substitution (see Allen and Hicks, 1934). This elasticity is defined as the percentage change in the ratio of the quantity of two factors to the percentage change in their price ratio allowing all other factors to adjust to their optimal level. While cost functions are the usual approach for estimating such elasticity, data on factor prices and total costs are generally not available at the firm level. Therefore, as suggested by Dewan and Min (1997), we estimate the substitution elasticities considering production functions. In the framework of a three input production function, the Allen partial elasticity of substitution (AES) for two inputs (R&D, denoted by $C$, and physical capital, denoted by $K$) is given by:

$$\sigma_{KC} = \frac{K \cdot f_K + L \cdot f_L + C \cdot f_C}{K \cdot C} \cdot \frac{\det(H_{KC})}{\det(H)} \tag{6}$$

where $f_K = \partial VA/\partial K$ is the marginal product of physical capital, $\det(H)$ is the bordered Hessian determinant of the $H$ matrix:

$$H = \begin{pmatrix} 0 & f_K & f_L & f_C \\ f_K & f_{KK} & f_{KL} & f_{KC} \\ f_L & f_{LK} & f_{LL} & f_{LC} \\ f_C & f_{CK} & f_{CL} & f_{CC} \end{pmatrix} \tag{7}$$

with $f_{KC} = \partial^2 VA/\partial K \partial C$ and $H_{KC}$ is the cofactor of the $H$ matrix associated with $f_{KC}$. The other partial elasticities of substitution (i.e. $\sigma_{KL}, \sigma_{CL}$), as well as partial elasticities with more than three inputs, are defined analogously.

If the AES is approximately equal to 1, then two goods are "normal" substitutes. Intuitively, the ratio of the factor quantities adjusts exactly in proportion to changes in their relative prices. If the AES is zero, the prices of the two factors have no influence on their ratio, while negative numbers indicate two factors are complements.

Both Cobb Douglas and Translog production functions together with the resulting elasticities are estimated considering Value Added as the output and three inputs, R&D capital, physical capital and labour. R&D capital is constructed from the R&D expenditures variable considered in Section 3 using the perpetual inventory method with a depreciation rate of 15% typically considered in the literature (see Beneito, 2001).[34] The labour input is measured as the number of employees minus the employees devoted to R&D activities. By

**33.** For the sake of comparability we will also present the estimates from the Cobb Douglas production function. In addition to the Translog, other production function specifications with unrestricted substitution elasticities between inputs are available in the literature (e.g. the CES-Translog proposed by Pollak et al., 1984). In this study we opt for the Ttranslog specification because it does not require non-linear estimation techniques (with the subsequent problems of local minima and convergence that seems to be specially relevant in our sample) and, more importantly, because the alternative CES-Translog imposes severe constraints that usually result in substitution elasticities close to 1 (see Hitt and Snir, 1999).

**34.** The initial stock is taken from the CBSO dataset, and it is measured by intangible capital based on R&D and IT (see Appendix for more details).

proceeding in this manner, we aim to avoid double counting of R&D investments as far as possible.[35] Finally, physical capital is also taken from the CBSO.

In addition to OLS, we consider an IV approach to address the potential endogeneity of the inputs with respect to output, and thus check the robustness of our findings to this issue. In particular, in the spirit of Arellano and Bond (1991), lagged levels of the inputs are used as instruments with the hope that current shocks to output are uncorrelated with past decisions on the input mix at the firm level. It should be noted here that the specifications in Table 11 do not include firm-specific effects in the production function. It is usual in the literature that estimates of R&D productivity based on within firm variation are typically small and statistically insignificant. This occurs because, as emphasised in Hall and Mairesse (1995), within estimates (based on either within groups or first differenced approaches) of R&D productivities might be biased due to systematical differences in the potential profitability of R&D in particular industries (e.g. electronics vs. agriculture) that cannot be captured through within firm variation in the data. Therefore, Hall and Mairesse (1995) argue that if the focus is on the economy-wide productivity gains that might be induced by R&D, estimates based on between firm-variation in R&D are more appropriate.[36]

Columns [1]-[2] and [5]-[6] of Table 9 present the elasticities resulting from the estimation of the two production functions (i.e. Cobb Douglas and Translog). The estimated R&D – output elasticity ($\eta_C$) of 3%-4% is in line with previous studies (e.g. Hall and Mairesse, 1995 for France, and Hall and Mairesse, 1996 for the US). Physical capital – output ($\eta_K$) and labour – output ($\eta_L$) elasticities are also comparable to previous work on firm level production functions (e.g. Blundell and Bond, 2000; Lichtenberg, 1995). Moreover, the second order terms in the Translog specification in columns [5] and [6] are jointly different from zero giving support to this functional form for estimating substitution elasticities. In particular, the F-test values are 48.35 and 40.34, respectively, with both p-values below 0.001.

Turning to Allen substitution elasticities in columns [5] and [6], we find that physical capital and R&D capital are substitutes ($\sigma_{CK} > 0$) while labour acts as a complement of both physical and R&D capital ($\sigma_{KL} < 0, \sigma_{CL} < 0$). Since the equations for the AES are non-linear functions of the estimated parameters as well as the quantities of factor inputs, we approximate the means and standard errors of the elasticity estimates using Monte Carlo simulations. In particular, the numbers reported in Table 9 are based on 1,000,000 random draws from a multivariate normal distribution, i.e., the asymptotic distribution of our parameter estimates.[37] Moreover, we follow earlier literature (Berndt and Wood, 1979) and evaluate the elasticities at the median values of the inputs.

Since the seminal paper by Griliches (1969), the complementarity between physical capital and skilled labour ($\sigma_{KL} < 0$) has received empirical support (see, for example, Duffy *et al.*, 2004). The underlying idea is that as countries develop, labour becomes more skilled and changes from being substitutable by capital to being highly complementary. Following the same argument, labour should also be complementary to R&D capital as we observe in our data ($\sigma_{CL} < 0$). In fact, Nelson and Phelps (1966) already studied complementarity between R&D and investments in human capital. Under their approach, labour is not simply another

**35.** Physical capital might also include R&D-related investments, meaning that the overall R&D elasticity would be $\eta_C^* = \eta_C + \lambda\eta_K$, where $\lambda$ is the share of R&D-related capital in the overall physical capital stock. If this share is low enough, our naive estimate $\eta_C$ would be close to the overall R&D elasticity.

**36.** In any event, our findings hold qualitatively when including firm effects.

**37.** Following Dewan and Min (1997) we discard random draws leading to elasticities outside the ±10 range.

factor of production, because it facilitates technology adoption and diffusion. As a result of R&D-labour complementarities, credit constraints during downturns might also be playing a role in labour investments by Spanish firms. According to the results in previous sections and the opportunity-cost theory, in the absence of credit constraints firms would invest in R&D during recessions since the opportunity costs of such investments is lower than during expansions. Moreover, higher R&D investments would also be accompanied by higher labour investments, as both inputs seem to enter as complements in the production function. Therefore, credit constraints might be hampering not only investment in R&D but also in labour, as discussed in previous sections. On the other hand, our finding that R&D capital is a net substitute of physical capital ($\sigma_{CK} > 0$) concur with the existing literature on capital-labour substitution (see Berndt, 1991 for an overview).

### *5.2 R&D and investment in other intangibles*

In columns [3]-[4] and [7]-[8] of Table 9 we consider four inputs in the production function instead of three. In particular, we consider a broader measure of intangible capital from the CBSO and split this capital into two different categories. On the one hand, $C_1$ refers to intangible capital based on innovation produced within the firm, including R&D as well as IT capital; on the other hand, $C_2$ refers to intangible capital resulting from innovation activities produced outside the firm i.e. patent acquisitions.

While output elasticities of physical capital and labour remain virtually unchanged with respect to the specification with three inputs, the overall elasticity of intangible capital ($\eta_{C1} + \eta_{C2}$) is around 4-5%, slightly higher than R&D capital, as expected, since intangible capital includes R&D as a component. Partial substitution elasticities confirm the results previously discussed, labour enters as a complement of both types of intangible capital in the production process ($\sigma_{C1L} < 0,\ \sigma_{C2L} < 0$). This indicates that irrespective of the source of innovation activities, be it inside or outside the firm, the activities should be accompanied by labour investments, so that under-investment in innovation might additionally generate under-investments in labour. Substitutability of physical and intangible capital appears to be confirmed for both types of intangible capital ($\sigma_{C1K} > 0,\ \sigma_{C2K} > 0$), especially for non-produced intangible capital. Finally, although not statistically significant, the Allen partial substitution elasticities for both intangible capital stocks point to substitution effects; firms decide whether to innovate by themselves or by acquiring innovation in the market (via patent acquisitions), as was suggested by the results of the previous section.

All in all, we would like to emphasise at this point that these results should be interpreted with caution as we are aware of the limitations of the approach considered in this section. In particular, substitution elasticities might easily be heterogeneous across industries or even across firms. Here we estimate homogeneous firm-level elasticities with the aim of providing some heuristic evidence of potential negative spillover effects of under-investment in innovation due to credit constraints through the channel of human capital accumulation.

## 6 Conclusions

We have used a Spanish firm-level panel data set over the period 1991-2010 to study the relationship between credit constraints and some firms' PEA over the business cycle. Among these activities, the focus of our paper has been on the main driver of innovation i.e. R&D investment, as well as on other measurable proxies of these activities, such as firms' training expenditures, and investment in other types of intangible assets.

A first step in our analysis has been to build a direct indicator of credit constraints. In order to do this, we matched two sources of firm-level information, namely, data for innovative firms in the Technological Innovation Panel (PITEC) from the National Institute of Statistics and data for non-financial corporations from the Banco de España's CBSO. This allowed us to estimate a probability of being credit constrained which is relevant for firms' R&D decisions, since we used the responses to a question in PITEC directly addressing this issue.

Our main results can be summarised as follows: i) the share of R&D spending in total investment is countercyclical without credit constraints, but this cyclical behaviour could be reversed as firms face tighter financial constraints; ii) the cyclical behaviour of a proxy for human capital accumulation – firms' spending on training – resembles that of the R&D share in the sense of being countercyclical, although it does not seem to be affected by our measure of credit constraints; iii) when we look at the levels of both physical and R&D investment, the former turns out to be highly procyclical, while the latter tends to be countercyclical; iv) these results hold when we use an alternative measure of R&D investment that only includes the portions of expenditures more likely to yield profits in the future and that also takes into account investment in software applications; v) a measure of other non-produced (within the firm) intangibles which is dominated by the behaviour of the purchases of patents (but which also includes other intangibles such as franchises and licenses), seem to be unrelated to the business cycle (in other words, acyclical) and not affected by credit constraints.

Finally, we draw attention to an issue that has been somehow neglected by the literature on the cyclical properties of R&D, which is the potential existence of indirect effects of business cycles on long-run growth stemming from the pattern of complementarities and substitutabilities among the different productive factors. Our findings show that R&D capital and labour are complementary, while R&D capital and physical capital seem to be substitute inputs. These results suggest that the overall cost to long-term growth of R&D under-investment during downturns due to the presence of credit constraints might probably be exacerbated by a resulting under-investment in human capital – although, as we have seen above, the share of training expenditures tends to behave countercyclically irrespective of the existence of financial constraints, which would mitigate this indirect effect.

As regards policy implications, countercyclical macroeconomic policies should provide support for R&D activities and productivity growth in firms that are more credit constrained and more dependent on external finance. However, this would not be the case for the other firms.

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## TABLES

**Table 1. Basic statistics from the CBSO database**

| Period | | 1991-2010 |
|---|---|---|
| Number of firms | | 3278 |
| Number of observations | | 26543 |
| Minimum of consecutive obs. per firm | | 3 |
| Median of consecutive obs. per firm | | 7 |
| Balanced? | | NO |
| % innovating | | 23.0% |
| Sector distribution | | |
| | Manufacturing | 44.5% |
| | Construction | 7.4% |
| | Services | 41.8% |
| | Other | 6.4% |
| Size distribution | | |
| | Small | 7.1% |
| | Medium | 47.1% |
| | Large | 45.9% |
| % exporting | | 55.3% |
| % public | | 7.4% |
| % stock market | | 6.1% |

Source: Banco de España.

**Table 2. Percentage of firms claiming to be financially constrained in PITE**

| Period average, % of constrained firms | | Matched sample: 2004-2009 |
|---|---|---|
| Overall | | 23% |
| By sector of activity | | |
| | Manufacturing | 21% |
| | Construction | 33% |
| | Services | 23% |
| | Other | 31% |
| By size | | |
| | Small | 28% |
| | Medium | 25% |
| | Large | 22% |
| By age | | |
| | < 10 years old | 27% |
| | Between 10 and 19 years old | 25% |
| | More than 20 years old | 20% |
| By debt ratio | | |
| | Lower than p10 (by sector and year) | 11% |
| | Higher than p90 (by sector and year) | 24% |
| By total debt burden | | |
| | Lower than p10 (by sector and year) | 13% |
| | Higher than p90 (by sector and year) | 24% |
| By cashflow | | |
| | Lower than p10 (by sector and year) | 32% |
| | Higher than p90 (by sector and year) | 20% |
| By collateral | | |
| | Lower than p10 (by sector and year) | 26% |
| | Higher than p90 (by sector and year) | 17% |

**Table 3. Results of the ordered probit for the probability of being financially constrained.**

| DV: probability of facing credit constraints | [1] Ordered probit | [2] Ordered probit | [3] Ordered probit | [4] Ordered probit | [5] Ordered probit | [6] Probit |
|---|---|---|---|---|---|---|
| Young | 0.02 | 0.02 | | | | |
| Small | 0.15*** | | 0.14*** | 0.18*** | 0.14*** | 0.01 |
| Age (in Ln) | | | -0.03** | -0.02 | -0.02** | -0.01 |
| Number of employees (in Ln) | | -0.01 | | 0.00 | | |
| Quoted | 0.01 | 0.01 | 0.02 | 0.02 | | 0.02 |
| Manufacturing | -0.11*** | -0.12*** | -0.11*** | | -0.11*** | |
| Construction (omitted) | | | | | | |
| Services | -0.08** | -0.08** | -0.08** | | -0.08** | |
| Leverage ratio | 0.13** | 0.12*** | 0.12*** | 0.12*** | 0.12*** | 0.17*** |
| Total debt burden | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** | 0.00 |
| Cashflow (Top 50%) | -0.05*** | -0.05*** | -0.05*** | -0.06*** | -0.05*** | -0.06*** |
| Collateral (Top 50%) | -0.03 | -0.02 | -0.03 | -0.01 | | -0.01 |
| GDP growth | -0.001 | -.001 | -0.001 | -0.00 | | 0.00 |
| 10 sector dummies | NO | NO | NO | YES | NO | YES |
| Observations | 3059 | 3059 | 3059 | 3059 | 3059 | 3059 |
| Clusters | 946 | 946 | 946 | 946 | 946 | 946 |
| % firms correctly placed | 71.4 | 72.2 | 72.1 | 71.3 | 72.3 | 71.9 |

Marginal effects for each covariate, computed at the average level of the other variables, are shown. *** denotes significant at 1%, ** significant at 5% and * significant at 10%. The dependent variable in the ordered probit model takes a value of 1 if the firms responded that a lack of external resources is of low importance in hampering innovative activities; a value of 2 if it is of medium importance and a value of 3 if it is very important. In the probit model (column [6]) the dependent variable is set to be one if a firm responded that the lack of finance was an important constraint for innovation.

**Table 4. Credit constraints and the cyclical behaviour of R&D investment**

| | Within-Groups estimator | | | | | | GMM estimator | | |
|---|---|---|---|---|---|---|---|---|---|
| Dep. variable: R&D exp./total investment | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] |
| $\Delta Sales_t$ | -0.010*** | -0.013*** | -0.014** | -0.035** | -0.041*** | -0.040** | -0.020 | -0.043** | -0.077*** |
| | (0.003) | (0.005) | (0.006) | (0.015) | (0.015) | (0.018) | (0.015) | (0.018) | (0.022) |
| $\Delta Sales_{t-1}$ | | -0.011*** | -0.015*** | | -0.050*** | -0.062*** | | -0.045*** | -0.076*** |
| | | (0.004) | (0.005) | | (0.014) | (0.017) | | (0.014) | (0.019) |
| $\Delta Sales_{t-2}$ | | | -0.006 | | | -0.034** | | | -0.040*** |
| | | | (0.005) | | | (0.016) | | | (0.013) |
| $CreditConst._{t-1}$ | | | | 0.079 | 0.083 | 0.104 | -0.002 | 0.064 | 0.146 |
| | | | | (0.058) | (0.058) | (0.072) | (0.145) | (0.137) | (0.121) |
| $\Delta Sales_t$ x $CC_{t-1}$ | | | | 0.073** | 0.093*** | 0.092** | 0.031 | 0.079** | 0.157*** |
| | | | | (0.032) | (0.035) | (0.043) | (0.033) | (0.040) | (0.048) |
| $\Delta Sales_{t-1}$ x $CC_{t-1}$ | | | | | 0.120*** | 0.159*** | | 0.091*** | 0.164*** |
| | | | | | (0.032) | (0.044) | | (0.031) | (0.044) |
| $\Delta Sales_{t-2}$ x $CC_{t-1}$ | | | | | | 0.096** | | | 0.091*** |
| | | | | | | (0.041) | | | (0.031) |
| No. of observations | 21676 | 17828 | 14196 | 17506 | 17485 | 13917 | 13892 | 13874 | 11085 |
| No. of firms | 3270 | 3141 | 2556 | 3103 | 3101 | 2523 | 2524 | 2521 | 2063 |
| Adjusted $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | | | |
| Sargan test (p-value) | | | | | | | 0.153 | 0.225 | 0.487 |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies.

**Table 5. Robustness to different definitions of R&D intensity**

| | Within-Groups estimator | | | | GMM estimator | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| Dependent variable: | R&D exp./GVA | R&D exp./Empl. | R&D exp./GOS | Ratio R&D Empl. | R&D exp./GVA | R&D exp./Empl. | R&D exp./GOS | Ratio R&D Empl. |
| $\Delta Sales_t$ | -0.041** | -0.746 | -0.354*** | -0.004** | -0.027** | -0.951** | 0.005 | -0.003*** |
| | (0.016) | (0.562) | (0.071) | (0.002) | (0.013) | (0.469) | (0.169) | (0.001) |
| $CreditConst._{t-1}$ | 0.019 | 1.421 | -2.196 | -0.019*** | -0.195* | -6.865* | -6.341* | -0.036** |
| | (0.021) | (1.593) | (1.749) | (0.006) | (0.100) | (4.141) | (3.772) | (0.014) |
| $\Delta Sales_t$ x $CC_{t-1}$ | 0.082** | 1.547 | 0.782*** | 0.007* | 0.052** | 1.827** | 0.002 | 0.006*** |
| | (0.032) | (1.154) | (0.169) | (0.004) | (0.025) | (0.914) | (0.382) | (0.002) |
| No. of observations | 17518 | 17518 | 17518 | 15572 | 13909 | 13909 | 13909 | 12288 |
| No. of firms | 3103 | 3103 | 3103 | 2879 | 2525 | 2525 | 2525 | 2333 |
| Adjusted $R^2$ | 0.01 | 0.05 | 0.01 | 0.01 | | | | |
| Sargan test (p-value) | | | | | 0.000 | 0.000 | 1.000 | 0.191 |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies.

GVA: gross value added; GOS: gross operating surplus.

**Table 6. The cyclical behaviour of physical investment: levels equation.**

| | Within-Groups estimator | | | GMM estimator | | |
|---|---|---|---|---|---|---|
| Dependent variable: $I_t$ / $K_{t-1}$ | [1] | [2] | [3] | [4] | [5] | [6] |
| $I_{t-1}$ / $K_{t-2}$ | -0.051 | -0.051 | -0.051 | 0.001 | -0.000 | -0.001 |
| | (0.046) | (0.046) | (0.046) | (0.005) | (0.005) | (0.005) |
| $\Delta Sales_t$ | 0.161*** | 0.162*** | 0.013 | 0.175** | 0.214*** | -0.046 |
| | (0.050) | (0.051) | (0.200) | (0.080) | (0.071) | (0.236) |
| $\Delta Sales_{t-1}$ | 0.241** | 0.247*** | 0.712 | 0.153*** | 0.151** | 0.353 |
| | (0.095) | (0.095) | (0.469) | (0.052) | (0.059) | (0.238) |
| $CreditConst._{t-1}$ | | -0.269 | -0.250 | | 3.404 | 1.593 |
| | | (0.314) | (0.320) | | (2.467) | (1.977) |
| $\Delta Sales_t$ x $CC_{t-1}$ | | | 0.376 | | | 0.837 |
| | | | (0.504) | | | (0.748) |
| $\Delta Sales_{t-1}$ x $CC_{t-1}$ | | | -1.339 | | | -0.497 |
| | | | (1.115) | | | (0.521) |
| No. of observations | 17726 | 17397 | 17397 | 14085 | 13811 | 13811 |
| No. of firms | 3134 | 3094 | 3094 | 2546 | 2515 | 2515 |
| Adjusted $R^2$ | 0.00 | 0.00 | 0.00 | | | |
| Arellano-Bond test for AR(2) (p-value) | | | | 0.099 | 0.102 | 0.102 |
| Sargan test (p-value) | | | | 1.000 | 1.000 | 1.000 |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies.

**Table 7. Heterogeneous Effects**

| | High Tech Firms ($D_t$=1) | | New Innov. Firms ($D_t$=1) | | High Growth Firms ($D_t$=1) | |
|---|---|---|---|---|---|---|
| Dep. variable: R&D exp./total investment | [1] | [2] | [3] | [4] | [5] | [6] |
| $\Delta Sales_t$ | -0.006** | -0.018 | -0.008*** | -0.025* | -0.010*** | -0.035** |
| | (0.003) | (0.013) | (0.003) | (0.014) | (0.003) | (0.015) |
| $\Delta Sales_t$ x $D_t$ | -0.110*** | -0.159 | -0.111** | -0.394 | 0.001 | 0.018 |
| | (0.040) | (0.213) | (0.057) | (0.262) | (0.014) | (0.054) |
| $CreditConst_{t-1}$ | | 0.083 | | 0.077 | | 0.080 |
| | | (0.058) | | (0.058) | | (0.058) |
| $\Delta Sales_t$ x $CC_{t-1}$ | | 0.039 | | 0.051 | | 0.076** |
| | | (0.028) | | (0.032) | | (0.033) |
| $\Delta Sales_t$ x $CC_{t-1}$ x $D_t$ | | 0.169 | | 1.113 | | -0.072 |
| | | (0.895) | | (0.939) | | (0.125) |
| No. of observations | 21676 | 17506 | 21676 | 17506 | 21676 | 17506 |
| No. of firms | 3270 | 3103 | 3270 | 3103 | 3270 | 3103 |
| Adjusted $R^2$ | | | | | | |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies.

**Table 8a. The cyclical behaviour of training expenditures.**

| | Within-Groups estimator | | | | GMM estimator | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: training exp. / train. exp.+ total investment | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| $\Delta Sales_t$ | -0.006** | -0.008* | 0.001 | 0.001 | -0.006** | -0.013*** | 0.008 | -0.007 |
| | (0.003) | (0.005) | (0.012) | (0.012) | (0.003) | (0.005) | (0.014) | (0.016) |
| $\Delta Sales_{t-1}$ | | -0.008** | | -0.120 | | -0.011*** | | -0.023** |
| | | (0.004) | | (0.010) | | (0.004) | | (0.011) |
| $CreditConst._{t-1}$ | | | -0.026 | -0.024 | | | 0.216 | 0.231 |
| | | | (0.036) | (0.036) | | | (0.126) | (0.147) |
| $\Delta Sales_t \times CC_{t-1}$ | | | -0.021 | -0.027 | | | -0.037 | -0.015 |
| | | | (0.031) | (0.035) | | | (0.034) | (0.040) |
| $\Delta Sales_{t-1} \times CC_{t-1}$ | | | | 0.012 | | | | 0.032 |
| | | | | (0.025) | | | | (0.027) |
| No. of observations | 19383 | 15847 | 15549 | 15528 | 15825 | 12525 | 12253 | 12235 |
| No. of firms | 3079 | 2919 | 2879 | 2877 | 2919 | 2364 | 2330 | 2327 |
| Adjusted $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | | | | |
| Sargan test (p-value) | | | | | 0.007 | 0.053 | 0.003 | 0.137 |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies.

**Table 8b. The cyclical behaviour of different intangible assets.**

| | Within-Groups estimator | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| Dependent Variable: | R&D investment and software applications | | | | Franchises, licenses and patents | | | |
| $\Delta Sales_t$ | -0.040** | -0.057*** | -0.127*** | -0.147*** | -0.011 | -0.024 | -0.044 | -0.034 |
| | (0.016) | (0.018) | (0.049) | (0.051) | (0.014) | (0.017) | (0.041) | (0.041) |
| $\Delta Sales_{t-1}$ | | -0.028 | | -0.133*** | | -0.020 | | 0.003 |
| | | (0.018) | | (0.048) | | (0.015) | | (0.042) |
| $CreditConst._{t-1}$ | | | 0.151 | 0.159 | | | 0.182 | 0.187 |
| | | | (0.212) | (0.210) | | | (0.193) | (0.193) |
| $\Delta Sales_t$ x $CC_{t-1}$ | | | 0.219* | 0.279** | | | 0.069 | 0.024 |
| | | | (0.123) | (0.132) | | | (0.112) | (0.115) |
| $\Delta Sales_{t-1}$ x $CC_{t-1}$ | | | | 0.320*** | | | | -0.069 |
| | | | | (0.120) | | | | (0.101) |
| No. of observations | 10638 | 9105 | 8934 | 8934 | 10638 | 9105 | 8934 | 8934 |
| No. of firms | 2275 | 2130 | 2101 | 2101 | 2275 | 2130 | 2101 | 2101 |
| Adjusted $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively. All regressions include sector dummies. The period covered in the regressions is 2001 - 2010.

**Table 9. Production Function Estimates**

| | Cobb-Douglas Specification | | | | Translog Specification | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| $\eta_K$ | 0.23*** | 0.24*** | 0.21*** | 0.21*** | 0.23*** | 0.23*** | 0.22*** | 0.21*** |
| | (0.008) | (0.009) | (0.010) | (0.011) | (0.007) | (0.008) | (0.010) | (0.010) |
| $\eta_L$ | 0.63*** | 0.62*** | 0.64*** | 0.64*** | 0.61*** | 0.59*** | 0.61*** | 0.61*** |
| | (0.012) | (0.013) | (0.013) | (0.015) | (0.011) | (0.013) | (0.013) | (0.015) |
| $\eta_C$ | 0.03*** | 0.04*** | | | 0.03*** | 0.04*** | | |
| | (0.004) | (0.004) | | | (0.004) | (0.004) | | |
| $\eta_{C1}$ | | | 0.01** | 0.02*** | | | 0.03*** | 0.03*** |
| | | | (0.005) | (0.007) | | | (0.006) | (0.007) |
| $\eta_{C2}$ | | | 0.03*** | 0.03*** | | | 0.01** | 0.01** |
| | | | (0.004) | (0.005) | | | (0.005) | (0.007) |
| $\sigma_{KL}$ | | | | | -0.73*** | -0.68*** | -0.55*** | -0.53*** |
| | | | | | (0.132) | (0.124) | (0.106) | (0.111) |
| $\sigma_{CK}$ | | | | | 2.14** | 1.78** | | |
| | | | | | (1.076) | (1.039) | | |
| $\sigma_{CL}$ | | | | | -2.60*** | -2.53*** | | |
| | | | | | (0.951) | (0.997) | | |
| $\sigma_{C1K}$ | | | | | | | 0.58 | 0.72* |
| | | | | | | | (0.49) | (0.53) |
| $\sigma_{C2K}$ | | | | | | | 1.39** | 1.26** |
| | | | | | | | (0.65) | (0.644) |
| $\sigma_{C1L}$ | | | | | | | -0.96*** | -1.06*** |
| | | | | | | | (0.387) | (0.446) |
| $\sigma_{C2L}$ | | | | | | | -1.32*** | -1.27** |
| | | | | | | | (0.527) | (0.570) |
| $\sigma_{C1C2}$ | | | | | | | 1.90 | 1.65 |
| | | | | | | | (2.885) | (3.079) |
| Obs. | 19734 | 16564 | 8424 | 6266 | 19734 | 16564 | 8424 | 6266 |
| Firms | 3169 | 3105 | 2060 | 1897 | 3169 | 3105 | 2060 | 1897 |
| Period | 91-09 | 91-09 | 01-09 | 01-09 | 91-09 | 91-09 | 01-09 | 01-09 |
| $R^2$ | 0.80 | - | 0.78 | - | 0.82 | - | 0.80 | - |

Standard errors clustered at the firm level in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%, respectively (from one-tailed tests in the case of substitution elasticities). All regressions include sector dummies. The Translog production function parameters are not reported for the sake of brevity. η refers to input elasticities and σ to Allen substitution elasticities. IV estimates are based on lagged levels of the inputs used as instruments for the contemporaneous input values.

## APPENDIX

**Table A1. Definition of variables**

| Variable | Definition |
|---|---|
| Dependent variable | |
| R&D/investment | Computed as the ratio between R&D spending and the sum of R&D spending and investment in physical capital |
| R&D/GVA | R&D spending divided by gross value added |
| R&D/GOS | R&D spending divided by gross operating surplus |
| R&D per capita | Real R&D spending divided by firm's average employment in year t, deflated with value-added sector deflator |
| R&D personnel | Percentage of total employment devoted to R&D activities |
| Tangible investment | Investment in tangible assets in year t over physical capital stock at the end of the previous period, t-1 |
| Training spending | Firm's spending in training divided by the sum of training spending and total (tangible and intangible) investment. Available from 1991 to 2007. |
| Investment in R&D and IT | Investment in R&D and IT with prospects of success and that can be assigned to a specific project. Computed as a share of total investment. Available from 2001 to 2009. |
| Investment in other intangibles | Investment in purchase of patent rights, goodwill, franchises and licenses, as a share of total investment. Available from 2001 to 2009. |
| Explanatory variables | |
| Sales growth | Growth rate of real sales of the firm in year t-1, deflated with a value-added deflator |
| Credit Constraint (CC) | Estimated probability that a firm faces financial obstacles which are serious enough to hamper its innovative activity. Computed using a two-stage approach. In the first stage, an ordered probit was run to estimate the relative importance of dummies for young age, small size, sector of activity, time dummies and the leverage ratio of the firm to explain a positive answer to a survey on financial obstacles to innovation (PITEC). The regression was run for firms both in the CBSO database and PITEC. In the second stage the estimated coefficients and value of the explanatory variables were used to estimate the probability of facing financial obstacles for innovation investment across all firms in the CBSO database. |
| Computing a direct indicator of financial obstacles | |
| FinObst | Response of firms in both PITEC and CBSO database to the question "During the two previous years, how important was the lack of finance from sources outside your enterprise for hampering your innovation activities?" Responses were ranked from 1 (high) to 3 (low) |
| Young | =1 if a firm has been in operations for less tna 5 years |
| Small | =1 if a firm has less than 50 employees |
| Quoted | =1 if firm is quoted in the stock market |
| Leverage ratio | Firm's interest-bearing external funds to internal funds, at t-1 |
| Cash-flow | Gross operating surplus plus financial interest received over stock of capital of the previous period, at t-1 |
| Total debt burden | Short-term interest-bearing debt plus interest paid over cashflow, at t-1 |
| Collateral | Share of tangible assets in total assets, at t-1 |

**Table A2. Sectors included in the empirical sample**

| CNAE 93 Rev.1* | Sector |
|---|---|
| 01, 02 | Agriculture and forestry |
| 05 | Fishing |
| 10, 11 | Mining, energy products |
| 13, 14 | Mining, other minerals |
| 15, 16 | Manufacture of food products, beverages and tobacco |
| 23 | Manufacture of coke and refined petroleum products |
| 24 | Manufacture of chemicals |
| 26 | Manufacture of other non-metallic products |
| 28, 28 | Manufacture of basic metals and fabricated metal products |
| 29 | Manufacture of machinery and equipment |
| 30, 31, 32, 33 | Manufacture of electrical and optical equipment |
| 34, 35 | Manufacture of motor vehicles, trailers and other transport equipment |
| 17, 18 | Manufacture of textiles, wearing apparel |
| 19 | Manufacture of leather and shoes |
| 20 | Manufacture of wood and cork |
| 22 | Manufacture of paper and printing |
| 25 | Manufacture of rubber and plastic products |
| 36, 37 | Other manufacturing |
| 40 | Electricity, gas, steam and air conditioning supply |
| 41 | Water collection, treatment and supply |
| 45 | Construction |
| 50, 51, 52 | Wholesale and retail trade |
| 60, 61, 62, 63, 64 | Transport and communications |
| 55 | Accommodation and food service activities |
| 70, 71, 72, 73, 74 | Real estate activities and professional services |

* Spanish National Classification of Economic Activities

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