Business Cycles and investment in intangibles: Evidence from Spanish firms

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Extended abstract:

This paper tests the opportunity-cost theory using a panel of Spanish firms during the period 1991-2009. According to such 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 long-term impact on productivity growth. Empirical evidence, however, finds that R&D is actually procyclical. This inconsistency between theory and empirics could be due to the existence of credit constraints at the firm level which impede firms to invest optimally. Following Aghion *et al.* (2007) we test this possibility allowing the impact of the cycle on R&D to vary between firms with different access to credit. For that purpose we construct an indicator of credit access using the survey information on that specific issue contained in the "Panel de Innovación Tecnológica", constructed from the Spanish answers to the Community Innovation Survey. We find that credit constraints prevent firms from undertaking R&D, even if it is optimal for them and positive for long-term productivity growth. We go one step further and explore whether other investment in intangibles, 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, differently from R&D investment, credit constraints seem not to impede such human capital investments during downturns. Investments in other intangibles, such as patent purchases, are found to be acyclical and not limited by financial constraints, which could suggest some kind of substitution between R&D and patent purchases over the cycle. We weakly confirm this possibility by means of an analysis of the existing relations of substitutability/complementarity across different intangible investments and between them and the traditional productive factors. We use for the analysis a unique database resulting from the merger of two different data sources. The first one is the extended balance-sheet information submitted by firms to the "Central de Balances" of the Bank of Spain, which contains detailed firm-level accounting information complemented with additional information on innovation activities or workforce characteristics. This type of information is provided on voluntary grounds annually by a large set of firms, about 3,000 after cleaning the data and requiring a minimum of 3 consecutive years of information, operating across all sectors of the economy. The second information source is the "Panel de Innovación Tecnológica", managed by the Statistics National Institute and containing detailed information at the firm level on the inputs and outputs of the innovation process, including some very valuable information on factors hampering innovation. We were able to match both sources of firm-level information using the fiscal identification number of firms.

1. Introduction

1.1. The aim of this paper

According to the opportunity-cost theory, the forgone cost of investing firm's resources in activities capable of enhancing long-run productivity growth is lower in recessions. Hence, it would be optimal for firms to invest more of the limited financial resources in, among other activities, R&D or to spend more of the working time in training in moments of distress. If this was the case, business cycles could have a positive impact on long-term productivity growth.[1]

However, most of the empirical studies linking R&D spending, one of the most important productivity-enhancing activities, and aggregate output find a procyclical relationship between both variables (see Wälde and Woitek 2004 and the references therein). Recent papers by Aghion and co-authors (2005, 2007) explain this apparent contradiction between the empirical evidence and what we would expect from theory by means of credit constraints. They show convincingly that in the absence of credit constraints the firm-level share of R&D in total investment moves countercyclically, as it is expected from theory. However, when one allows the effect of the cycle to differ for firms with different access to credit markets, that countercyclical relation vanishes for financially constrained firms. The argument is that in moments of distress, firms' current revenue decreases, which might improve the difficulties to access external finance of financially vulnerable firms. If access to credit decreases in recessions for those firms, so does their R&D investment.

These theoretical predictions have important policy implications: credit market imperfections may be impeding firms to decide optimally the amount of resources to devote to production and to R&D, with potentially important consequences for long-run economic growth. Hence, policy intervention, to alleviate those credit constraints, could be desirable in those circumstances. Given the relevance of this result one wonders whether other productivity-enhancing activities follow the same type of pattern, or move in line with what one would expect according to the opportunity-cost theory. There is not much on this in the literature, being an exception Nickell *et al.* (1995), who study the cyclical performance of other managerial and organizational changes –apart from the introduction of new technologies–, and Geroski and Gregg (1997), who consider the effect of recessions on other intangible investments, apart from R&D spending, such as training and marketing spending.

The aim of this paper is to take Aghion *et al.* (2007) as a starting point and expand its analysis in several directions. First, we test the validity of its conclusions for the case of Spain during the period 1991-2009, a broader period than the one considered in that paper (1993-2004), which allows us to include the 1991-1993 crisis and, above all, the two first years of the current financial crisis. Secondly, we expand the analysis to explore

[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).

the cyclicality of other productive enhancing activities besides R&D spending, like training or patent rights purchases. Apart from the fact that it helps to accumulate human capital, on-the-job training spending has been proven to be a relevant input in the innovation process (see Lopez-Garcia and Montero 2011).[2] As regards the purchase of patent rights, most of the empirical work reviewed in the next section focus 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 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 credit crunch.

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 no credit constraints. Moreover, as expected from the theory, other productivity-enhancing activities, in particular on-the-job training, follow the same countercyclical pattern as R&D. In other words, in recessions it is optimal for firms to devote some time of their hoarded labour to accumulate human capital rather than to produce, given the lower opportunity cost of the former. As it has been established elsewhere, 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 other 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 non-produced capital 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" (CB) 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 training, for a sample of about 3,000 Spanish firms during the period 1991-2009. However, as it has long been established in the literature, balance sheet based indexes of financial constraints like cash-flow measures might present some limitations (Kaplan and Zingales 1997 and Whited and Wu 2006). Given the importance for our analysis of correctly measuring financial constraints, we have resorted to survey data to

[2] Lopez-Garcia and Montero (2011) use data for a sample of Spanish firms to find that firm's share of skilled workers and job training real spending per worker enhance significantly the capacity of the firm to absorb and implement into its own production process knowledge generated elsewhere, with the result of a higher probability of innovation. The stability of the workforce, on the other hand, proxied by the share of temporary contracts in the firm, was found to have as well a significant although direct impact on one firm's probability of innovation.

construct a direct indicator of innovation-related financing obstacles for all firms in the 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 CB database.

The remaining of the section overviews the literature on business cycles and long-term growth and takes a first look at the available aggregate evidence on the cyclicality of R&D spending in Spain. 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 replicates the analysis of Aghion *et al.* (2007) using several measures of firms' R&D activities and section 4 expands the analysis to include investment in other intangibles. Section 5 deepens the study of the substitution/complementarity of the different factor of production, putting special emphasis on the relations between the different investments in intangibles and, finally, section 6 concludes.

1.2. Literature overview

In the big picture, this paper is about the effect of business cycles on long-run economic growth. For a long time, both phenomena were seen as independent developments. Long-term growth was driven by exogenous technological progress, and transitory fluctuations around the trend were caused by demand or monetary variables. This separation between short and long-term fluctuations came to an end with the emergence of the real business cycle theory (Kydland and Prescott 1982), which stressed the importance of exogenous technological shocks as drivers of real business cycles. The possibility that business cycles could actually affect technological progress and, therefore, long-term growth started taking shape only as part of the growing interest for endogenous growth (Romer 1990). The core of the endogenous growth theory is that technological progress itself is the outcome of optimal decisions taken by the agents in a given economic environment concerning innovation and human capital accumulation. If demand fluctuations affect those optimal decisions, business cycles can have an impact on technological progress and long-term growth.

Since the 1990s there have been a lot of theoretical and empirical papers attempting 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, that is, 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 or "lame duck" theory, based on the original work of Schumpeter, in the 1930s, and reshuffled 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.

Another such theory is the opportunity-cost approach, which claims that there is a number of productivity enhancing activities (PEA), such as the reorganization of production, on-the-job training or research and development activities, that detract resources from production, that is, that are costly in terms of forgone production, and whose benefit is spread in the future. Given the fall in revenue from normal productive activities during recessions, the opportunity costs of such activities will be at its lowest in times of crisis. Hence, 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.

The empirical literature testing for the impact of cycles on Total Factor Productivity (TFP), a measure that should capture the effects of the PEA implemented during recessions, finds in general support for the opportunity-cost theory (see Bean 1990, Gali and Hammour 1991, Saint-Paul 1993 and Malley and Muscatelli 1996)[3]. However, there are very few papers identifying which PEA significantly rises during recessions. The obvious candidate would be research and development activities (R&D), which are labour intensive and therefore, as stated by the opportunity-cost theory, detract labour resources from other productive activities.[4] The forgone cost of such activities would fall during recessions and, therefore, we would expect firms to devote more resources to R&D in such troubled times.

However, there is overwhelming empirical evidence on the procyclicality of R&D spending, which is at odds with the opportunity-cycle theory (see, for example, Wälde and Woitek 2004, and Geroski and Walters 1995, and the references therein). There are a number of papers aiming at explaining this unexpected procyclicality of R&D. Barlevy (2007) explains it on the basis of the existence of spillovers of R&D activities. He claims that there is limited appropriability of new products, which means that there is only a short window of time to rip rents 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). Another explanation of the observed procyclicality of R&D is offered in Ouyang (2011). In that paper it is argued that there is an aggregation bias in the studies of the cyclical behavior of aggregate R&D resulting from the fact that not all industry cycles are perfectly synchronized. If aggregate R&D is dominated by the movements of a certain industry which happens not to be synchronized 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.

However, the most promising explanation of the failure of the opportunity-cost theory is offered by Aghion *et al.* (2007). Their claim is that the opportunity cost argument would hold only in the absence of credit constraints. If a firm depends on external resources to perform R&D activities, when 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 hit 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

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[3] All of the papers above, with the exception of Bean (1990), use a semi-structural VAR approach due to the endogenous nature of both economic cycles and productivity in the spirit of Blanchard and Quah (1989).

[4] Many of the employees involved in R&D are not scientists, but supporting staff that could be used in other parts of the production process.

moves countercyclically, as expected by the opportunity cost theory. However, when one allows that effect to vary between firms who are financially constrained and those who are not, the result changes: the R&D investment share turns procyclical in those firms more dependent on external sources to finance innovation. This same result is also found, using the CIS database, by Bovha-Padilla *et al.* (2009) for Slovenian firms.

Some authors have focused their attention on non-R&D PEAs. As we mentioned above, 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 reorganization and new technologies. They find that worsening performance tends to be followed by an increase in the probability that the firm introduces new technology as well as other managerial and organizational changes. However, higher financial pressure only decreases the likelihood of introducing new technology, while it has no significant impact on other changes in organization 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.

1.3. Macroeconomic evidence

The purpose of this section is to have a cursory look at the aggregate evidence on business cycles and innovation in Spain. We are able to use annual data for the period from 1969 to 2009 for that purpose, which is largely dictated by data availability on R&D expenditures. Data on business enterprise R&D expenditures in current prices are from the Spanish National Institute of Statistics. On the other hand, annual data for real GDP and its price deflator –which we use to convert nominal R&D into real magnitudes–, are from the OECD database on National Accounts.

Figure 1 contains the annual growth rate of real GDP and real business R&D for the period 1970-2009. During this period, the average growth rate for both variables has been 2.9% and 8.5%, respectively, while their volatility, measured by the standard deviation of the growth rate, has been 2.2% and 9.8%, respectively. In other words, as one would expect, R&D investment volatility exceeds that of real GDP by a factor of 4.5, which is similar to the excess volatility of physical investment. Moreover, from Figure 1 it can be observed a clear positive co-movement between these two series, which would suggest a pro-cyclical relationship between R&D activities and final output.

Further evidence on the cyclical behavior of R&D is provided following along the lines of Wälde and Woitek (2004). Trend and cyclical components of GDP and R&D investment are obtained by applying a Hodrick-Prescott filter to the logarithms of these variables.[5] Then correlation coefficients and corresponding standard errors are obtained by

[5] As suggested by Maravall and del Río (2001) the smoothing parameter for this filter is set at 10.

regressing the cyclical components of real R&D expenditures on the cyclical components of real GDP, correcting the standard errors for heteroskedasticity and autocorrelation à la Newey and West (1987). Besides, we estimate the same coefficients for the first-differenced series, also including a constant term.

Table 1 contains the results of this estimation exercise. The contemporaneous correlations are positive and statistically significant in both cases, which show the pro-cyclical nature of contemporaneous R&D expenditures. Leading and lagging GDP does not change the message; correlation coefficients are all positive and overall statistically significant, except for the cases of the lead of HP-filtered GDP. All in all, these results provide strong evidence for a procyclical behavior of private R&D expenditures.[6]

One might argue, however, that the above-computed correlation is an unconditional one and that the correct correlation between GDP and R&D should be estimated conditioning on the fundamental determinants of R&D investment. In line with Rafferty (2003), we estimate a crude error-correction model between R&D expenditures and GDP, which we expand by including public R&D expenditures ($RDgov_t$), deflated with the GDP deflator, and a measure of cash flows, private non-financial corporation's gross operating surplus[7] (CF_t). This model takes the form:

$$\Delta RD_t = \alpha + \beta_1 \Delta GDP_t + \beta_2 \Delta GDP_t \Delta CF_{t-1} + \beta_3 \Delta CF_{t-1} + \gamma_0 \Delta RDgov_t + \delta(RD_{t-1} - \rho GDP_{t-1}) + \varepsilon_t \tag{1}$$

If business R&D is procyclical, as implied by results from Table 1, then one would expect that $\beta_1>0$, while $\beta_2<0$ would imply that looser financial constraints, as captured by the indirect impact of increasing internal resources on financing conditions, reverse such procyclicality. The sign of γ_0 will determine whether public R&D investment crowds in or crowds out business corporations R&D.[8]

Table 2 contains the results from estimating equation (1).[9] In column [1] it is shown the model without the financial channel ($\beta_2=\beta_3=0$), while in column [2] we allow for it. The most interesting aspect of this simple regression analysis is the fact that the short run coefficient for GDP is positive and statistically significant and, besides, quite similar to the unconditional correlations in Table 1 (around 2.0), which would confirm the procyclicality of R&D expenditures. Accounting for credit constraints through the cash flow variable has the potential to reverse the results, since the interaction with GDP growth is negative and statistically significant. If we take the coefficient on $\Delta GDP_t \cdot \Delta CF_{t-1}$ from column [2], the short run elasticity of business R&D to GDP would change sign from positive to negative for increases in the gross operating surplus exceeding 4.0 percentage points in a year,

[6] These results would contradict the findings in Estrada and Montero (2009) who, using a SVAR approach in which the endogenous variables are real GDP, the GDP deflator, business R&D and public sector R&D, find some evidence that private R&D is countercyclical in Spain.

[7] Data on gross operating surplus come from the accounts of institutional sectors in the Statistical Bulletin of the Bank of Spain.

[8] We have used two additional variables on internal resources for the aggregate Spanish non-financial corporations as proxies for the existence of cash flow effects and financial constraints. First, we adjusted the gross operating surplus by net interest payments received. Second, we computed gross corporate savings by additionally adjusting the latter measure by direct taxes and net dividend payments (received minus paid). Regression results were qualitatively similar.

[9] Availability of the data for gross operating surplus restricts the estimation simple to the period 1981-2009.

which is a particularly common phenomenon, as it has a frequency of 41.4% in the sample period. In other words, for those years in which firms' internal resources grow at rates over 4% in real terms, R&D spending becomes countercyclical.

Moreover, the contemporaneous impact of public R&D is positive and statistically significant, thus pointing to the possibility that government R&D crowds in private R&D investment, as found in Estrada and Montero (2009).

According to this preliminary look at aggregate data, R&D spending seems to be procyclical. However, as section 3 will show in a more detailed way, the co-movement between R&D and GDP depends crucially on the presence of credit constraints at the firm level. This is corroborated by aggregate evidence when the correlation between GDP growth and R&D investment accounts for the presence of cash flow effects. Indeed, for large enough growth rates of firms' internal resources (a situation where credit constraints appear less likely), R&D expenditures seem to be countercyclical. But first, the next section describes the firm-level database used in the econometric exercise.

2. *Data and issues in measuring financial constraints*

2.1. The "Central de Balances" from the Banco de España

The main source of data is the firm-level information provided by the "Central de Balances" (CB) of the Banco de España. Since 1983 and in order to follow the economic situation of the private non-financial sector, the CB has been compiling and publishing aggregate information of firms' balance sheets, as well as some other additional information –of great interest for our study– such as the value of sales, employment, training spending or, since 1991, R&D expenditures as well as investment in other intangibles.

After cleaning the data,[10] we selected those firms with at least three consecutive years of information. The result is an unbalanced panel covering the period 1991-2009 and containing information for 3,183 firms (25,635 observations all in all). Table 3 shows the basic characteristics of the CB 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 in moments of distress. If that was the case, even if those firms found it optimal to increase investment in productivity-enhancing activities during recessions due to their lower opportunity costs, they might not be able to do so because they have no access to the required long-term external funds. One of the novelties of this paper is that we are able to exploit survey

[10] We drop observations with 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 p99 and p1, respectively) and substitute their value by the corresponding threshold.

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

information from the Technological Innovation Panel (PITEC) to obtain a direct indicator of financing constraints faced by firms in the Central de Balances database. PITEC is a longitudinal database constructed on the basis of the annual Spanish responses to the Community Innovation Survey (CIS) and 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 2007 for reasons of comparability.[13]

Although access to the database is public and free for researchers, observations are anonymized 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 CB. The merger was positive for about one-fifth of the observations –around 600 matched observations per year– in the CB database between 2004 and 2007.

2.3. Constructing a proxy for financial obstacles to innovate

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 low 3 (low). The procedure to construct a credit constraint indicator for all firms in the 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 do this exercise for firms who replied the PITEC questionnaire and had a positive matching in the CB database. The set of explanatory variables includes those suggested by the literature, such as age, size, the 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 CB database.

There are 2,382 matched observations in the CB, about 600 firms per year during the period 2004-2007. Of all matched observations, 948 stated that the question on the importance of the lack of external resources for innovation was non-relevant for them, because they did not perform innovative activities. Hence, we are left with 1,400

[12] PITEC is sponsored by *Fundación Española para la Ciencia y la Tecnología* (FECYT) and 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 (less than 200 employees) non-innovative firms.

observations over the period. Table 4 shows the percentage of those claiming to be financially constrained (in order to carry out innovative projects) according to size, age, sector of activity, collateral and debt ratio.[14]

On average, 24% of firms think that the lack of external funds is seriously hampering their innovative activities (hence, they are financially constrained). If we distinguish by sector of activity, the highest proportion of constrained firms is to be found in the construction sector, and the lowest in manufacturing. Small firms (less than 50 employees) and very young firms (less than 5 years) seem to be also more financially constrained. Lastly, firms with a very low share of tangible assets (than can be collateralized) and those with high debt ratios 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, Hubbard and Petersen (1988). According to that paper, the presence of asymmetric information and agency costs in financial markets drives a wedge between the cost of internal and external funds. There is already a very large literature devoted to identifying the determinants of firms' financial constraints. Those determinants 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, Gertler and Gilchrist 1996, Hernando and Martinez-Carrascal 2003 and Atanasova and Wilson 2004). Lastly, there are a number of papers finding that variables related to access to alternative sources of finance, like 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 analyze which of the firm's characteristics suggested by the literature make it more likely for firms to be financially constrained when it comes to invest in innovation. For that purpose, we assume that the firms' underlying response can be described by the following equation:

$$FinObst_{i,t} = \sum_i \emptyset_i (FirmCharacteristics)_{i,t} + \varphi_t + \mu_j + \varepsilon_{i,t} \qquad (2)$$

where $FinObst_{it}$ is the answer (in a scale from 1 to 3) reported by firm i at time t to PITEC's question on financing obstacles and $FirmCharacteristics_{it}$ is a vector of firms' attributes. We include year dummies (φ_t) and control for industry-specific effects including a set of sector dummies ($\mu_j\psi$).[15] Since omitted firm characteristics might cause the error term to be correlated for observations corresponding to the same firm, we allow for clustered error terms. Given that the dependent variable is categorical and can take 3 values, we use an ordered probit model to estimate equation (2). We have also tried, however, a

[14] We consider that a firm is financially constrained if it reports lack of external finance to be 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, becoming only relevant when financial pressure exceeds a certain threshold (see, for example, Hernando and Martinez-Carrascal 2003).

[15] We include a dummy for manufacturing, construction and services or a dummy for 25 more disaggregated sectors of activity, see appendix.

probit model where the dependent variable takes the value of 1 if the firm responds that the lack of finance is important and 0 otherwise. As suggested by the literature, we have included among the explanatory variables a set of dummies for size (=1 if small), age (=1 if young) and being quoted in the stock market (=1 if quoted).[16] 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 between external funds with cost 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 total assets.[17]

Table 5 reports the marginal effects from the estimation of the first-stage regressions. The first column includes all explanatory variables, including a set of 25 industry dummies; the second column substitutes the 25 sectors of activity by 3 main sectors of activity; column (3), our preferred specification, keeps in the regression only the significant covariates and the broad sectors of activity, while column (4) repeats the analysis using a probit model. Results are fairly robust and in accordance to what we could a priori expect from theory. Being young increases the probability of facing financial obstacles when it comes to innovation by about 13 percentage points (pp), while being small increases it by almost 30 pp. The impact of age is very similar to that found in Coluzzi *et al.* (2008), in spite of the different databases used, whereas the impact of size is clearly larger here. This could be reflecting the fact that the results of Coluzzi *et al.* (2008) are averaged across 5 European countries,[18] whereas ours refer only to Spain. In fact, Artola and Genre (2011) find, using the 2009 and 2010 firm-level responses to the ECB-EU SME survey on access to finance, that Spanish micro and small firms are those with the highest risk of facing financial constraints, about 36 pp more than the risk faced by large firms, a figure quite similar to ours. In this simple framework, the sector of activity is not significant and, among the variables reflecting the financial position of the firm, only the firm's leverage ratio turns out to be, consistently, important.

The next step is to use the estimated coefficients to estimate the probability of facing credit constraints to innovate for all firms in our CB sample. We have computed several proxies to financial obstacles using the coefficients obtained from all the specifications above in order to test for the robustness of the results.

2.4. Testing the estimated proxy for financial obstacles

The last step is to test the goodness of the constructed variable proxying financial constraints. For that purpose we use the information at our disposal in the CB about the stock of firms' bank credit, which is the main source of external finance of Spanish firms. Moreover, we can distinguish between short and long term bank loans. Given that the proxy for financial restrictions is computed using firms' answer to a question related to obstacles for innovation, we expect the variable to have a larger impact on long-term bank credit, given the long-run nature of innovative activities. Table 6 shows the results of a very simple and illustrative exercise whereby the annual growth of long-term bank credit

[16] We have also tried with some other definitions for age and size, but results were fairly similar.
[17] For a detailed definition of variables please refer to the appendix.
[18] France, Germany, Italy, Portugal and Spain.

and total one of each firm in the CB database is regressed on the proxies constructed from the coefficients of Table 5 for the probability of being credit constrained, and the lagged growth of firms' real sales. To make it easier to interpret, each column includes the proxy for financial constraints constructed from the coefficients of the corresponding column in Table 5.

These very simple regressions show that our proxies for financial constraints are better suited to explaining variations in long-term credit, as expected. They are fairly similar across specifications, both in terms of signs, magnitude of coefficients and significance, with the exception of the regression with a full set of 25 sector dummies.

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

3.1. Baseline specification

In this section we use our preferred measure of credit constraints to test an empirical specification very similar to that in Aghion *et al.* (2007), which is derived from a theoretical model in the spirit of Aghion *et al.* (2005). In this model, firms can choose between short-run capital investment and long-term R&D investment and, besides, innovation requires that firms survive short-run liquidity shocks. In order to cover these shocks, firms can rely only on their short-run earnings plus 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. Thus, R&D investment should be expected to be more procyclical in firms facing tighter credit constraints.

In order to test this theoretical prediction, we follow closely Aghion *et al.* (2007) and estimate the subsequent specification:

$$\frac{RD_{it}}{RD_{it}+I_{it}} = \beta_0 + \beta_1 \Delta s_{it} + \beta_2 \Delta s_{it-1} + \beta_3 \Delta s_{it-2} + \gamma_0 CC_{it-1} + \gamma_1 \Delta s_{it} CC_{it-1} + \gamma_2 \Delta s_{it-1} CC_{it-1} + \\ + \gamma_3 \Delta s_{it-2} CC_{it-1} + \mu_t + \eta_i + u_{it} \qquad (3)$$

where RD_{it} represents R&D investment, I_{it} physical investment, CC_{it-1} the probability that firms are credit constrained, and Δs_{it} the (log) variation in firms' real sales. We also account for time dummies (μ_t) and firms' fixed effects (η_i), while u_{it} represents the usual error term.

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

Finally, we do not expect a particular sign for γ_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, γ_0 may be either positive or negative.

As regards the estimation method, we estimate the equation with the Within Groups (WG) estimator, given that it is more reasonable to assume a framework with fixed effects, where unobserved firm heterogeneity may potentially be correlated with independent variables. Moreover, in order to avoid potential simultaneity bias arising from the joint determination of sales and both types of investment, we use an instrumental variables methodology, in particular, the GMM estimator (Arellano and Bond, 1991). In this method the instruments are appropriate sets of lagged values of the variables, which make it particularly attractive in our setting, where it is difficult to find appropriate external instrumental variables.

Table 7 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 are negative and statistically significant at conventional levels for the variation in current sales, 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 are correctly signed, but their statistical significance is less 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 and 0.5 percentage points (pp) that same year. Besides, if we take into account the results under column [9], that effect would be quite persistent and in the order of 0.5 pp. This magnitude is quite important, since it implies a cut of 7 pp of the average R&D share.[19]

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 equally affected by credit constraints as physical investment. However, when CC_{it-1} is interacted with the sales shock variables, we obtained results consistent with the theoretical predictions, i.e., the share of R&D turns less countercyclical in the presence of financial constraints, a result that is robust only for the variation in current sales. Indeed, for those firms where $CC_{it-1} \rightarrow 1$, the sensitivity to real sales growth would be $\beta_1+\gamma_1 \cong 0$, in other words, the R&D share would be roughly acyclical.

[19] One has to notice 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 average R&D share would amount to 21 pp.

3.2. Robustness checks

In order to check the robustness of our results, we have carried out a set of additional empirical exercises of which we present a selection. First, we have studied whether using an alternative definition of the R&D share changes the results. Second, on passing, 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 8 reports the results from estimating equation (3) using different normalizations 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 employment. Some way or another, all these ratios reflect a trade-off between a productivity-enhancing activity (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 8 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 on the variation of sales is negative and 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 (Δs_{it} x 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' gross value added and output (both measured at basic prices and deflated with the sectoral value added deflator). Results in Table 7 turned out to be qualitatively similar. Besides, we have used other measures of credit constraints derived from the same framework described in Section 2 (using results from columns (1), (2) and (4) in Table 5). Again, results in Table 7 would be qualitatively and quantitatively similar.[20]

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.

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

[20] For the sake of brevity, we do not report these results, but they are available upon request.

$$\frac{I_{it}}{K_{it-1}} = \alpha_0 + \alpha_1 \frac{I_{t-1}}{K_{t-2}} + \beta_1 \Delta s_{it} + \beta_2 \Delta s_{it-1} + \gamma_0 CC_{it-1} + \gamma_1 \Delta s_{it} CC_{it-1} + \gamma_2 \Delta s_{it-1} CC_{it-1} + + \mu_t + \eta_i + u_{it} \quad (4)$$

where I_{it} is physical investment, K_{it-1} denotes the stock of physical capital and the rest of variables are defined as in equation (3). This equation would be similar in spirit to those that test for the presence of financial constraints.[21] In line with this literature, we expect physical investment to be procyclical ($\beta_1,\beta_2>0$) and negatively affected by credit constraints ($\gamma_0,\gamma_1,\gamma_2<0$). Again, we estimate this equation with the WG and GMM estimators.

Table 9 shows the results from estimating equation (4). As it can be seen, physical investment turns out to be procyclical, but with a lag. 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.[22] This could be the result of the way the indicator of credit constraints has been built, given it is based on answers of firms about obstacles to innovation. Indeed, in Aghion *et al.* (2007) their proxy for credit constraints –based on the credit history of firms- turns out to be negative and significant, while the interactions are not, which means that physical investment is negatively affected by financial constraints no matter the firm's location in the business cycle.

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's assume we are in a recession; then 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 being either increasing or decreasing (although to a less extent that physical investment). Regression results not reported –and which use a similar specification as equation (4)– show that indeed the *level* of R&D investment would be weakly countercyclical.[23] 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 fairly consistent with the view espoused by the "Opportunity Cost Approach".

4. Other intangible investment

At the firm level we have found that the share of R&D expenditures over total investment is countercyclical as suggested by opportunity-cost theory, although only in the absence of 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.

[21] See the pioneering work of Fazzari et al. (1988) and the subsequent literature that developed afterwards.

[22] This result also holds when we do not include the lag of physical investment –which is not significant itself.

[23] We mean "weak" in the sense of having negative coefficients with low statistical significance, i.e. p-values around 0.25.

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) are two of the few papers looking at the effect of cycles on human capital accumulation finding that, according to the opportunity-cost theory, firms might also shift resources to human capital building through job training of hoarded labour 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 a proxy of the level of credit constraints faced by the firm (see Section 2.3 for more details on the construction of such a proxy) in order to check the role of the latter on the cyclicality of the dependent variable.

Table 10a presents the results for estimating the cyclicality of training expenditures. In particular, we consider as dependent variable the ratio of training expenditures[24] over training expenditures plus total investment 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 on human capital formation within the firm.

More concretely, in columns [1] and [2] of Table 10a we estimate a negative effect from the cycle on training expenditures. While the contemporaneous effect in column [1] is only marginally significant (p-value = 0.21), once we include a lag of the cycle in column [2] the countercyclicality of training expenditures is significant at the 1% level, suggesting that job training expenditures seem to counter-cyclically react with a lag to the change in sales. This basically indicates that firms devote a larger share of their investment resources to human capital building 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 favor 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 over total investment of around 0.1 percentage points during the current and the subsequent years. This effect represents 2.5% of the average training expenditure share in our sample.

Columns [3] and [4] in Table 10a provide evidence that credit constraints do not seem to play any role in human capital investments for hoarded labour within the firm. In particular, we observe that neither the credit constraints proxy nor its interaction with the cycle result 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 of

[24] We have information on training spending from 1991 to 2007, so we will use a shorter sample to carry out the analysis of that variable.

hoarded labour 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.

Finally, columns [5] to [8] of Table 10a confirm these results using an alternative panel GMM estimator taking into account the potential endogeneity of firm sales and credit constraints with respect to training expenditures. In particular, following the approach considered in the previous section based on Arellano and Bond (1991), we allow for feedback effects from training expenditures to sales and credit constraints using lagged levels of these variables as instruments for their first-differences. The significance and the magnitude of the coefficient estimates based on this GMM estimator closely resemble the ones previously obtained in the within-groups estimates. 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 such productivity-enhancing activity.

Above and beyond R&D and training, there are other investments in intangibles which could enhance firms' productivity performance in the future. In 2001, the Accounting rules changed in Spain and obliged firms to input in different entries of their balance sheet investment in R&D and IT applications[25] and other intangible investments "not produced" at the firm, which include mostly the purchase of the right to use and exploit external inventions, that is patents purchase. This distinction, which can only be made for the period 2001-2009, 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 production of innovation activity. 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 10b 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 over total investment. The results are consistent with those presented in Table 7, the ratio is counter cyclical as expected from the opportunity cost theory, but becomes procyclical beyond a certain level of credit constraints. This reinforces the robustness of Section 3's results, 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 pattern of cyclicality of investment in R&D.

Columns [5]-[8] of Table 10b repeat the estimation of our baseline specification, but considering now the share of investment in patent rights over total investment as dependent variable (so-called "non-produced" –within the firm– intangibles, because they are either purchased or a byproduct of firms' activities). The cyclical behavior of these intangibles investments is different from that of other intangibles, as it seems to be

[25] 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 "Central de Balances" 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 succeed in some sense.

unrelated to the business cycle, i.e. acyclical. Despite the coefficient on sales being generally negative, it is 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 the volume of sales 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 in moments 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.

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

5.1. R&D capital versus physical capital and labour

Despite the overall benefits from R&D investment are widely accepted, how to efficiently promote such investment remains a challenge to policy makers. In previous sections we found some evidence in favor 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 to combine machinery, knowledge capital, and human capital in a complementary fashion.

In the definition by Edgeworth,[26] 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 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 productivity-enhancing activity. Thus, this would have an additional indirect effect on long-term growth, via less accumulation of human capital.

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 appealing of the popular Cobb-Douglas production function, it is not suitable for our purpose here since it constraints the substitution elasticities between

[26] See Hicks (1970) for an overview.

different inputs to unity. Therefore, our methodological framework departs from a Translog production function (Christensen *et al.*, 1973) at the firm level as follows:

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

where VA_{ijt} refers to the Value Added in constant Euros 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, δ_t and μ_j include a set of time and sector dummies respectively. While the time dummies aim to capture the common factors affecting all firms in 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 when all the coefficients of the quadratic terms are set equal to zero.[27]

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:

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

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:

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

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. $\sigma_{\mathrm{KL}}, \sigma_{\mathrm{CL}}$), 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

[27] For the sake of comparability we will also present the estimates from the Cobb Douglas production function. Besides 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 Translog 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 impose severe constraints that usually result in substitution elasticities close to 1 (see Hitt and Snir, 1999).

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).[28] The labour input is measured as the number of employees minus the employees devoted to R&D activities. By doing so, we aim to avoid double counting of R&D investments to the extent possible.[29] Finally, physical capital is also taken from "Central de Balances".

Additionally 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. An important remark here is 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 is so because, as emphasized 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 interest 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.[30]

Columns [1]-[2] and [5]-[6] of Table 11 present the elasticities resulting from the estimation of the two production functions (i.e. Cobb Douglas and Translog). The estimated R&D – output elasticity (η_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 (η_K) and labour – output (η_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-

[28] The initial stock is taken from the "Central de Balances" dataset, and it is measured by intangible capital based on R&D and IT (see the appendix for more details).

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

[30] In any event, our findings qualitatively remain when including firm effects.

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 5 are based on 1,000,000 random draws from a multivariate normal distribution, i.e., the asymptotic distribution of our parameter estimates.[31] 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 complementary between physical capital and skilled labour ($\sigma_{\mathrm{KL}} < 0$) has received empirical support estimating aggregate production functions (see, for example, Duffy *et al.*, 2004). The underlying idea is that as countries develop, labour becomes more skilled and change from being substitutable with capital to being highly complementary. Following the same argument, labour should also be complementary to R&D capital as we observe in our data ($\sigma_{\mathrm{CL}} < 0$). In fact, Nelson and Phelps (1966) already studied complementarity between R&D and investments in human capital. Within their approach, labour is not simply another 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 as 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 ($\sigma_{\mathrm{CK}} > 0$) 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 11 we consider four inputs in the production function instead of three. In particular we consider a broader measure of intangible capital from "Central de Balances" 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 rights acquisition.

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 ($\eta_{\mathrm{C1}} + \eta_{\mathrm{C2}}$) is around 4-5%, a bit 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 ($\sigma_{\mathrm{C1L}} < 0$, $\sigma_{\mathrm{C2L}} < 0$). This indicates that regardless the source of innovation activities, inside or outside the firm, they should be accompanied by labour investments, so that under-investment in innovation might additionally generate under-

[31] Following Dewan and Min (1997) we discard random draws leading to elasticities out of the ±10 range.

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, despite not being statistically significant, the Allen partial substitution elasticities for both intangible capital stocks point to substitution effects between them; firms decide whether to innovate by itself or acquire innovation in the market (via patent rights acquisition), as it was suggested by the results of the previous section.

All in all, we remark 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 1991-2009 to study the relationship between credit constraints and some firms' productivity-enhancing activities 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 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 Bank of Spain's Central de Balances. This allowed us to estimate a probability of being credit constrained relevant for firms' R&D decisions, as we used the responses to a question in PITEC that directly addresses this issue.

Our main results can be summarized as follows: i) the share of R&D spending over total investment is countercyclical without credit constraints, but this cyclical behavior could be reversed as firms face tighter financial constraints; ii) 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 acyclical or mildly countercyclical; iii) 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; iv) a measure of other non-produced (within the firm) intangibles which is dominated by the behavior of the purchases of patent rights (but which also includes other intangibles such as goodwill, franchises, and licenses), seem to be unrelated to the business cycle (in other words, acyclical) and not affected by credit constraints; v) on the other hand, the cyclical behavior of a proxy for human capital accumulation –firms' training spending– 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.

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 regardless the existence of financial constraints, which would mitigate such indirect effect–.

As regards policy implications, countercyclical macroeconomic policies should provide support to 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 rest of firms. This notwithstanding, no robust macroeconomic policy implications can be deducted without previously analyzing the asymmetry of business cycles. As stressed in Rafferty and Funk (2004), it might be argued that whether R&D is procyclical or countercyclical is of little interest if the effect on R&D of a recession is offset by the effect on R&D of the following expansion. One has to take into account whether expansions are longer than recessions and whether output lost in a recession is larger than output gained during an expansion. If symmetry is breached, then business cycles do not necessarily cancel out and they can either increase or decrease R&D. Thus, we leave for future research the study of asymmetries and their potential implications for stabilization policies.[32]

[32] Even under the assumption of symmetric business cycles effects on R&D, if innovative activities are countercyclical, then policymakers would still want to smooth expansions in order to avoid negative effects on PEAs, and might reconsider the policy of eliminating (or smoothing out) recessions, since that policy would reduce inventive activity and, hence, productivity growth.

REFERENCES

Aghion, P. and G. Saint-Paul (1998): “On the Virtue of Bad Times: An Analysis of the Interaction between Economic Fluctuations and Productivity Growth”, *Macroeconomic Dynamics*, vol. 2, 322-344.

Aghion, P., G.-M. Angeletos, A. Banerjee and K. Manova (2005): “Volatility and Growth: Credit Constraints and Productivity-enhancing Investment”, NBER Working Papers, No. 11349.

Aghion, P., P. Askenazy, N. Berman, G. Cette, and L. Eymard (2007): “Credit Constraints and the Cyclicality of R&D Investment: Evidence from France”, *Journal of the European Economic Association*, forthcoming.

Allen, R. and J. Hicks (1934): “A Reconsideration of the Theory of Value II”, *Economica*, vol. 1, 196-219.

Arellano, M. and S. Bond (1991): “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations”, *Review of Economic Studies*, vol. 58, 277-297.

Artola, C. and V. Genre (2011): “Euro area SMEs under Financial Constraints: Belief or reality?” unpublished paper.

Atanasova, C. and N. Wilson (2004): “Disequilibrium in the UK corporate loan market”, *Journal of Banking and Finance*, vol. 28, 595-614.

Barlevy, G. (2007): “On the Cyclicality of Research and Development”, *The American Economic Review*, vol. 97(4), 1131-1164.

Bean, C. (1990): “Endogenous Growth and the Procyclical Behavior of Productivity”, *European Economic Review*, vol. 34, 355-363.

Beneito, P. (2001): “R&D Productivity and Spillovers at the Firm Level: Evidence from Spanish Panel Data”, *Investigaciones Economicas*, vol. 25, 289-313.

Benito, A. and I. Hernando (2002): “Extricate: Financial Pressure and Firm Behaviour in Spain”, Banco de España Working Papers no. 0227.

Bernake, B., Gertler, M. and S. Gilchrist (1996): “The Financial Accelerator and the Flight to Quality”, *Review of Economics and Statistics*, vol. 78, 1-15.

Berndt, E. (1991): “The Practice of Econometrics: Classic and Contemporary”, Addison Wesley, Reading, MA.

Berndt, E. and O. Wood (1979): “Engineering and Econometric Interpretations of Energy-Capital Complementarity”, *The merican Economic Review*, vol. 69, 342-354.

Blanchard, O.J. and D. Quah (1989): “The Dynamic Effects of Aggregate Demand and Supply Disturbances”, *The American Economic Review*, vol. 79, 655-673.

Blundell, R. and S. Bond (2000): “GMM Estimation with Persistent Panel Data: An Application to Production Functions”, *Econometric Reviews*, vol. 19, 321-340.

Bovha-Padilla, S., J.P. Damijan and J. Konings (2009): “Financial Constraints and the Cyclicality of R&D investment: Evidence from Slovenia”, LICOS Discussions Paper 239/2009. Katholieke Universiteit Leuven.

Caballero, R. and M. Hammour (1996): "On the Timing and Efficiency of Creative Destruction," *The Quarterly Journal of Economics*. Vol. 111(3), 805-52.

Christensen, L., D. Jorgenson, and L. Lau (1973): “Transcendental Logarithmic Production Frontiers”, *The Review of Economics and Statistics*, vol. 55, 28-45.

Coluzzi, C., Ferrando, A. and C. Martinez-Carrascal (2008): “Financing Obstacles and Growth: An Analysis for Euro Area non-Financial Corporations”, Documento de Trabajo 0836, Banco de España.

Dewan, S. and C. Min (1997): “The Substitution of Information Technology for Other Factors of Production: A Firm Level Analysis”, *Management Science*, vol. 43, 1660-1716.

Duffy, J., C. Papageorgiou, and F. Perez-Sebastian (2004): “Capital-Skill Complementarity? Evidence from a Panel of Countries”, *The Review of Economics and Statistics*, vol. 86, 327-344.

Estrada, A. and J.M. Montero (2009): “R&D Investment and Endogenous Growth: a SVAR Approach”, Documento de Trabajo 0925, Banco de España.

Fazzari, S.M., R.G. Hubbard and B.C. Petersen (1988): “Financing Constraints and Corporate Investment”, *Brookings Papers on Economic Activity*, vol. 1, 141-203.

Galí, J. and M. Hammour (1993): “Long-Run Effects of Business Cycles”, unpublished manuscript.

Geroski, P.A. and C.F. Walters (1995): “Innovative Activity over the Business Cycle”, *The Economic journal*, vol. 105, 916-928.

Geroski, P.A. and P. Gregg (1997): Coping with Recession: UK company performance in adversity, Cambridge University Press.

Gilchrist, S. and C. Himmelberg (1995): “Evidence on the Role of Cash-Flow for Investment”, *Journal of Monetary Economics*, vol.36, 541-572.

Griliches, Z. (1969): “Capital-Skill Complementarity”, *The Review of Economics and Statistics*, vol. 51, 465-468.

Hall, R. (1991): “Recessions as Reorganizations”, NBER Macroeconomic Annual.

Hall, B. and Mairesse, J. (1995): “Exploring the Relationship between R&D and Productivity in French Manufacturing Firms”, *Journal of Econometrics*, vol. 65, 263-293.

Hall, B. and Mairesse, J. (1996): "Estimating the Productivity of R&D: An Exploration of GMM Methods using data on French and US Manufacturing Firms", NBER Working Paper 5501.

Hall, B. (2002): "The Financing of Research & Development", NBER Working Paper No. 8773.

Harrison, A. and M. Mcmillan (2003): "Does Direct Foreign Investment Affect Foreign Domestic Constraints?" *Journal of International Economics*, vol. 61(1), 73-100.

Hernando, I. and C. Martinez-Carrascal (2003): "The Impact of Financial Variables on Firms' Real Decisions: Evidence from Spanish Firm-Level Data", Documento de Trabajo 0319, Banco de España.

Hicks, J. (1970): "Elasticity of Substitution Again; Substitutes and Complements", *Oxford Economic Papers*, vol. 22, 289-296.

Hitt, L. and E. Snir (1999): "The Role of Information Technology in Modern Production: Complement or Substitute to Other Inputs?", unpublished manuscript.

Kaplan, S., and L. Zingales (1997): "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?", *Quarterly Journal of Economics,* vol. 107, 169-215.

Kydland, F.E. and E.C. Prescott (1982): "Time to Build and Aggregate Fluctuations", *Econometica,* vol. 50, 1345-1370.

Lichtenberg, F. (1995): "The Output Contributions of Computer Equipment and Personnel: A Firm Level Analysis", *Economic Innovations and New Technology*, vol. 3, 201-217.

López-García, P. and J.M. Montero (2010): "Understanding the Spanish Business Innovation Gap: the Role of Spillovers and Firms' Absorptive Capacity", Documento de Trabajo 1015, Banco de España. Forthcoming in *Economics of Innovation and New Technology*.

Malley, J. and V.A. Muscatelli (1999): "Business Cycles and Productivity Growth: Are Temporary Downturns Productive or Wasteful?" *Research in Economics,* vol. 53, 337-364.

Maravall, A. and A. del Río (2001): "Time Aggregation and the Hodrick-Prescott Filter", Documento de trabajo 0108, Banco de España.

Nelson, R. and E. Phelps (1966): "Investment in Humans, Technological Difussion, and Economic Growth", *The American Economic Review*, vol. 56, 69-75.

Newey, W.K. and K.O. West (1987): "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica*, vol. 55, 703-708.

Ouyang, M. (2011): "On the Cyclicality of R&D", *The Review of Economics and Statistics*, vol. 93(2), 542-553.

Pollak, R., R. Sickles, and T. Wales (1984): “The CES-Translog: Specification and Estimation of a New Cost Function” *The Review of Economics and Statistics*, vol. 66, 602-607.

Rafferty, M.C (2003): “Do Business Cycles Influence Long-Run Growth? The Effect of Aggregate Demand on Firm-Financed R&D Expenditures”, *Eastern Economic Journal*, Vol. 29(4), 607-618.

Romer, P. (1990): “Endogenous Technological Change," *Journal of Political Economy*, 98(5), 71-102.

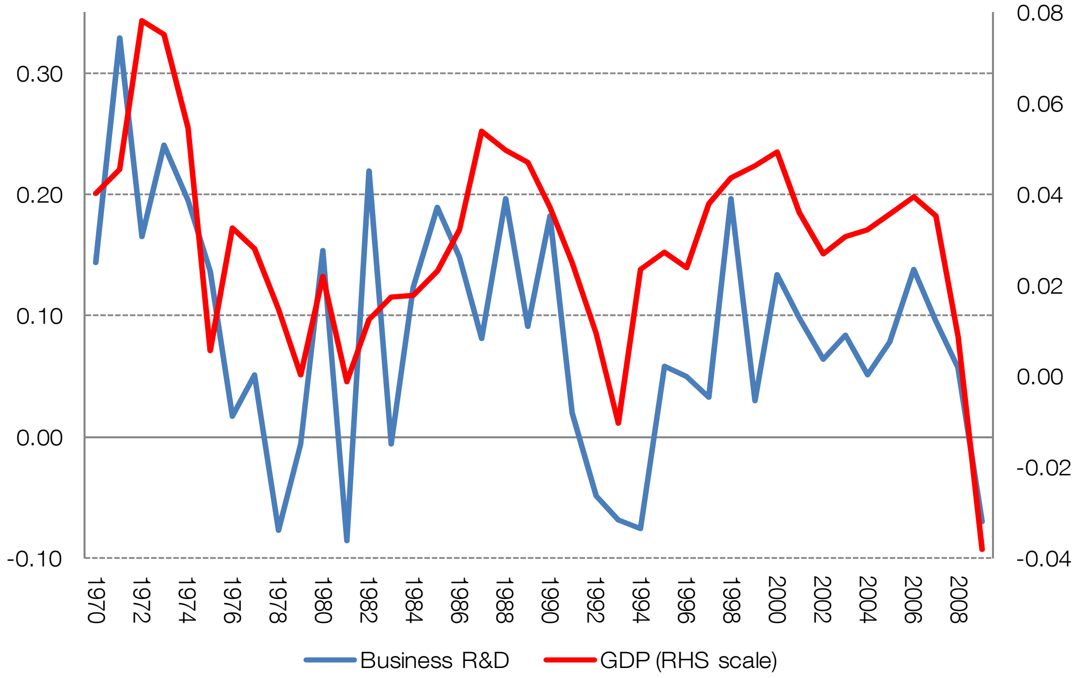
Saint-Paul, G. (1993): “Productivity Growth and the Structure of the Business Cycle”, *European Economic Review*, vol. 37, 861-890.

Wälde, K. and U. Woitek (2004): “R&D Expenditure in G7 Countries and the Implications for Endogenous Fluctuations and Growth”, *Economics Letter*, vol. 82, 91-97.

Whited, T.M., and G. Wu (2006): “Financial Constraints Risk”, *Review of Financial Studies, v*ol. 19, 531-559.

FIGURES

Figure 1: Annual growth rate of GDP and business R&D expenditures



TABLES

Table 1: Correlation coefficients between GDP and business R&D spending

Correlation coefficients between GDP and business R&D expenditures for Spain (1969-2009)

	GDP:				
	lag 2	**lag 1**	**lag 0**	**lead 1**	**lead 2**
Hodrick-Prescott filtered series	1.32***	2.48***	2.24***	1.12	0.12
	0.24	0.50	0.61	0.75	0.57
1st differenced series	1.32**	2.53***	2.76***	2.19***	1.45**
	0.52	0.83	0.75	0.58	0.60

HAC standard errors and covariance (Newey and West, 1987); *, **, ***: denote statistical significance at 10%, 5% and 1% levels

Table 2: ECM estimation

Estimated coefficients for the ECM (1981-2009)

	[1]	**[2]**
Constant	-4.357**	-3.366**
	(1.784)	(1.454)
ΔGDP_t	2.420***	1.985***
	(0.618)	(0.614)
ΔGDP_t x ΔCF_{t-1}		-50.12***
		(16.95)
ΔCF_{t-1}		2.086***
		(0.531)
$\Delta RDgov_t$	0.661**	1.090***
	(0.285)	(0.263)
Error-correction term	-0.299***	-0.255***
	(0.103)	(0.083)
GDP level$_{t-1}$	2.201***	2.092***
	(0.160)	(0.168)
Adjusted R^2	0.470	0.660
S.E. of regression	0.063	0.051
F-statistic	7.199	10.058
Prob(F-statistic)	0.001	0.000
Durbin-Watson stat	2.127	2.691

*, **, ***: denote statistical significance at 10%, 5% and 1% levels

Table 3: Basic statistics from the Central de Balances database

Period average		*Full sample: 1991-2009*
Number of firms		3183
Number of observations		25635
Minimum nº of consecutive obs. per firm		3
Median nº of consecutive obs. per firm		7
Balanced?		no
% innovating		23
Sector distribution		
	manufacturing	45.2
	construction	7.4
	services	41.0
	other	6.4
Size distribution		
	Small	6.9
	Medium	48.2
	Large	45.0
% exporting		55.6
% public		7.4
% stock market		6.1

Source: Banco de España

Table 4: Percentage of firms claiming to be financially constrained in PITEC

Period average, % constrained firms		*Matched sample: 2004-2007*
Overall		24%
by sector of activity		
	manufacturing	22%
	construction	42%
	services	24%
	other	29%
By size		
	Small	56%
	Medium	25%
	Large	23%
By age		
	< 5 years	37%
	Between 5 and 9	28%
	Between 10 and 19	29%
	More than 20	21%
By collateral		
	Lower than p10 (by sector and year)	34%
	Higher than p90 (by sector and year)	24%
By debt ratio		
	Lower than p10 (by sector and year)	8%
	Higher than p90 (by sector and year)	31%

Table 5: Results of the ordered probit for the probability of being financially constrained. Marginal effects. Matched observations PITEC-CB.

	(1)	(2)	(3)	(4)
DV: probability of facing financial obstacles1	Ordered probit	Ordered probit	Ordered probit	Probit
Young	0.11*	0.14***	0.13***	0.100
Small	0.37***	0.37***	0.27***	0.25***
Quoted	0.03	0.03		
Manufacturing		-0.03	-0.06	-0.05
Construction		0.08	0.06	0.09
Services		-0.05	-0.07	-0.05
Leverage ratio	0.17***	0.18***	0.18***	0.24***
Total debt burden	0.00	0.00		
Cash-flow	0.00	0.00		
Colateral	0.02	0.04		
Time dummies	yes	yes	yes	yes
25 sector dummies	yes	no	no	no
Observations	1300	1392	1392	1392
Clusters	473	495	495	495

Marginal effects for each covariate, computed at the average level of the rest of variables, are shown. *** denote significant at 1%, ** significant at 5% and * significant at 10%. [1] The dependent variable in the ordered probit model takes de value 1 if the firms respond that lack of external resources is of low importance hampering innovative activities, 2 if it is of medium importance and 3 if it is very important. In the probit model (column (4)), a firm is financially constrained if responded that the lack of finance was an important factor, and unconstrained otherwise.

Table 6: Testing the relevance of the variable proxying for financial constraints

DV: Long-term bank credit growth rate	(1)	(2)	(3)	(4)
Probability of facing financial obstacles	-6.7	-6.8**	-6.9**	-5.7**
Lagged growth of real sales	4.1	4.1	4.1	4.1
DV: Total bank credit growth rate				
Probability of facing financial obstacles	-9.1	-7.6	-11.3	-12**
Lagged growth of real sales	4.3	4.2	4.2	4.2
Observations	14516	14516	14910	14910
Clusters	2835	2835	2890	2890

Table7: Credit constraints and the cyclical behaviour of R&D investment

Dep. variable: ratio of R&D exp. over total investment	Within-groups estimator						GMM estimator		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\Delta Sales_t$	-0.009***	-0.012**	-0.012**	-0.027***	-0.030**	-0.031**	-0.027**	-0.025	-0.048**
	(0.003)	(0.005)	(0.006)	(0.010)	(0.012)	(0.014)	(0.014)	(0.020)	(0.022)
$\Delta Sales_{t-1}$		-0.004	-0.008		-0.011	-0.020		-0.004	-0.034*
		(0.007)	(0.006)		(0.020)	(0.016)		(0.028)	(0.020)
$\Delta Sales_{t-2}$			-0.012			-0.037*			-0.052**
			(0.008)			(0.022)			(0.021)
$CreditConst._{t-1}$				0.001	0.000	-0.001	0.033	0.021	-0.047
				(0.026)	(0.026)	(0.036)	(0.065)	(0.063)	(0.071)
$\Delta Sales_t$ x CC_{t-1}				0.042**	0.046**	0.048**	0.039*	0.033	0.065*
				(0.017)	(0.020)	(0.024)	(0.023)	(0.033)	(0.036)
$\Delta Sales_{t-1}$ x CC_{t-1}					0.019	0.035		0.002	0.048
					(0.033)	(0.027)		(0.046)	(0.033)
$\Delta Sales_{t-2}$ x CC_{t-1}						0.062*			0.083**
						(0.035)			(0.034)
No. Observations	21674	18019	14367	18089	18019	14367	14434	14367	11505
No. of firms	3169	3166	2577	3169	3166	2577	2582	2577	2113
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01			
Sargan test (p-value)							0.742	0.133	0.536

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%. All regressions include sector and time dummies, and a constant, not reported.

Table 8: 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.*
$\Delta Sales_t$	-0.024**	-0.657	-0.021***	-0.003**	-0.024**	-0.832*	-0.023***	-0.003***
	(0.012)	(0.559)	(0.007)	(0.002)	(0.012)	(0.436)	(0.009)	(0.001)
$CreditConst._{t-1}$	-0.006	0.920	-0.002	-0.003	-0.006	-0.025	-0.031	0.006
	(0.027)	(1.126)	(0.015)	(0.004)	(0.027)	(1.696)	(0.038)	(0.005)
$\Delta Sales_t \times CC_{t-1}$	0.035*	1.162	0.033***	0.005*	0.035*	1.202*	0.034**	0.004**
	(0.020)	(0.907)	(0.011)	(0.003)	(0.020)	(0.717)	(0.014)	(0.002)
No. Observations	18089	18089	18083	16000	14434	14434	14424	12678
No. of firms	3169	3169	3169	2941	2582	2582	2582	2388
Adjusted R^2	0.02	0.03	0.01	0.02				
Sargan test (p-value)					0.000	0.000	1.000	0.798

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%. All regressions include sector and time dummies, and a constant, not reported.

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

Table 9: The cyclical behaviour of physical investment: levels equation.

Dependet variable: I_t / K_{t-1}	Within-groups estimator			GMM estimator		
	[1]	[2]	[3]	[4]	[5]	[6]
I_{t-1} / K_{t-2}	-0.043	-0.043	-0.043	-0.003	-0.004	-0.004
	(0.045)	(0.045)	(0.045)	(0.008)	(0.007)	(0.007)
?$Sales_t$	0.056	0.055	-0.184	0.139	0.141	-0.107
	(0.126)	(0.128)	(0.303)	(0.090)	(0.093)	(0.217)
?$Sales_{t-1}$	0.148***	0.149***	0.289*	0.092**	0.095**	0.124
	(0.042)	(0.042)	(0.172)	(0.043)	(0.044)	(0.095)
$CreditConst._{t-1}$		-0.145	-0.137		0.260	0.409
		(0.408)	(0.400)		(0.507)	(0.546)
?$Sales_t$ x CC_{t-1}			0.576			0.577
			(0.468)			(0.400)
?$Sales_{t-1}$ x CC_{t-1}			-0.310			-0.068
			(0.355)			(0.201)
No. Observations	18003	18003	18003	14352	14352	14352
No. of firms	3166	3166	3166	2576	2576	2576
Adjusted R^2	0.00	0.00	0.00			
Arellano-Bond test for AR(2) (p-value)				0.638	0.641	0.654
Sargan test (p-value)				1.000	1.000	1.000

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%. All regressions include sector and time dummies, and a constant, not reported.

Table 10a: The cyclical behaviour of training expenditures.

Dependent variable: ratio of training exp. over train. exp.+ total investment	Within-groups estimator				GMM estimator			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\Delta Sales_t$	-0.005	-0.011***	-0.009	-0.015	-0.004	-0.013***	-0.002	-0.019
	(0.004)	(0.004)	(0.009)	(0.010)	(0.004)	(0.005)	(0.009)	(0.012)
$\Delta Sales_{t-1}$		-0.011***		-0.021**		-0.013***		-0.025**
		(0.004)		(0.009)		(0.004)		(0.011)
$CreditConst._{t-1}$			-0.026	-0.026			0.041	0.010
			(0.026)	(0.027)			(0.066)	(0.065)
$\Delta Sales_t$ x CC_{t-1}			0.004	0.01			-0.005	0.016
			(0.018)	(0.021)			(0.016)	(0.022)
$\Delta Sales_{t-1}$ x CC_{t-1}				0.023				0.028
				(0.017)				(0.020)
No. Observations	19501	15930	16000	15930	15930	12611	12678	12611
No. of firms	3111	2938	2941	2938	2938	2383	2388	2383
Adjusted R^2	0.01	0.01	0.01	0.01				
Sargan test (p-value)					0.022	0.194	0.008	0.317

Robust standard errors in parentheses. *, **, *** denote significance levels at 10%, 5% and 1%. All regressions include sector and time dummies, and a constant, not reported.

Table 10b: 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***				***Goodwill, franchises and advances, and patent rights***			
$\Delta Sales_t$	-0.025	-0.039**	-0.078**	-0.102**	-0.010	-0.023	-0.015	-0.009
	(0.016)	(0.019)	(0.040)	(0.042)	(0.015)	(0.018)	(0.034)	(0.035)
$\Delta Sales_{t-1}$		-0.017		-0.130***		-0.020		0.002
		(0.019)		(0.048)		(0.016)		(0.036)
$CreditConst._{t-1}$			0.136	0.128			0.035	0.031
			(0.130)	(0.130)			(0.094)	(0.093)
$\Delta Sales_t$ x CC_{t-1}			0.108	0.164**			-0.004	-0.034
			(0.072)	(0.079)			(0.069)	(0.073)
$\Delta Sales_{t-1}$ x CC_{t-1}				0.247***				-0.052
				(0.088)				(0.065)
No. Observations	10719	9378	9378	9378	10719	9378	9378	9378
No. of firms	2159	2159	2159	2159	2159	2159	2159	2159
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%. All regressions include sector and time dummies, and a constant, not reported. The period covered in the regressions is 2001 - 2009.

Table 11: Production function estimates with intangible capital.

	Cobb-Douglas				Translog			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
η_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)
η_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)
η_C	0.03***	0.04***			0.03***	0.04***		
	(0.004)	(0.004)			(0.004)	(0.004)		
η_{C1}			0.01**	0.02***			0.03***	0.03***
			(0.005)	(0.007)			(0.006)	(0.007)
η_{C2}			0.03***	0.03***			0.01**	0.01**
			(0.004)	(0.005)			(0.005)	(0.007)
σ_{KL}					-0.73***	-0.68***	-0.55***	-0.53***
					(0.132)	(0.124)	(0.106)	(0.111)
σ_{CK}					2.14**	1.78**		
					(1.076)	(1.039)		
σ_{CL}					-2.60***	-2.53***		
					(0.951)	(0.997)		
σ_{C1K}							0.58	0.72*
							(0.49)	(0.53)
σ_{C2K}							1.39**	1.26**
							(0.65)	(0.644)
σ_{C1L}							-0.96***	-1.06***
							(0.387)	(0.446)
σ_{C2L}							-1.32***	-1.27**
							(0.527)	(0.570)
σ_{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% (from one-tailed tests in the case of substitution elasticities). All regressions include sector and time dummies, and a constant, not reported. 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 te sum of R&D spending and investment in physical capital
R&D/GVA	R&D spending over gross value added
R&D/GOS	R&D spending over gross operating surplus
R&D per capita	Real R&D spending over 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 over 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 success prospects 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 important 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 CB and PITEC. In the second stage the estimated coefficients and value fo the explanatory variables were used to estimate the probability of facing financial obstacles for innovation investment across all firms in the CB database.
Computing a direct indicator of financial obstacles	
FinObst	Response of firms in both PITEC and CB 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 less than 5 years of operations
Small	=1 if a firm has less than 50 employees
Quoted	=1 if firm is quaoted in the stock market
Leverage ratio	Firm's external funds with cost to internal funds, at t-1
Cash-flow	Gross operating surplus plus financial interests received over stock of capital of the previous period, at t-1
Total debt burden	Short-term debt with cost plus interests paid over cash-flow, at t-1
Collateral	Share of tangible assets over total assets, at t-1

Table A2: Sector composition of the empirical sample

NACE 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, traileers 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	Accomodation and food service activities
70, 71, 72, 73, 74	Real state activities and professional services