estructura econòmica
ECONOMÍA APLICADA II

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December 2014

Working Papers in Applied Economics

WPAE-2014-11

ECONOMÍA APLICADA II

VNIVERSITAT DE VALÈNCIA

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ISSN 2172-3036

DOES R&D PROTECT SMEs FROM THE HARDNESS OF THE CYCLE? EVIDENCE FROM SPANISH SMEs (1990-2009)

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Abstract: This paper analyses whether undertaking R&D activities allows SMEs to attenuate the negative impact of recessions on productivity. In contrast to other studies we use a firm level indicator of the cycle based on firms' own perceptions, while total factor productivity is obtained using a control function methodology in which we recognise the potential role that R&D experience might have in shaping future firms' productivity. The analysis is performed using a representative sample of Spanish SMEs for the period 1990-2009. Results show both that R&D activities render positive productivity returns, and that performing R&D helps to alleviate the negative effects of downturns on productivity. Additionally, R&D seems to have a countercyclical effect upon SME's productivity over the business cycle, as we find that SMEs R&D productivity premium in recessions doubles that of expansions.

Key words: TFP, business cycle, R&D.

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1. Introduction.

The role of small and medium enterprises (SMEs henceforth) as a driving force for economic growth has been broadly recognised. SMEs are crucial to the revitalization of the economy as well as to the preservation and generation of employment,[1] which is especially important when the economy undergoes severe circumstances. Fostering SMEs productivity, as a way to ensure their survival and growth in the economy, is therefore a major issue, both to managers and policy makers.

Amongst the determinants of firms' productivity growth, the key role of innovation has also been widely acknowledged. Starting with the seminal works of Schumpeter (1934, 1942) and his concept of creative destruction as the mechanism driving and shaping the evolution of markets and economic growth, a general consensus has emerged that Research and Development (henceforth R&D) is one of the main drivers of firm's performance and competitiveness (Griliches, 1980; Porter and Ketels, 2003). In particular, previous studies, both at the theoretical and empirical level, have shown how R&D investment decisions are affected by the business cycle (Hall, 1991; Barlevy, 2007). However, there is a scarce literature looking at the difference in the effectiveness of R&D upon performance between periods of recession and expansion (exceptions being Steenkamp and Fang, 2011; and Srinivassan *et al.*, 2011). This study aims to fill this gap in the literature by analysing the extent to which R&D decisions affect productivity performance in SMEs in recessive periods.

The opportunity cost theory (Hall, 1991, Aghion and Saint-Paul, 1998) claims that it is optimal for firms to devote resources to R&D activities during recessive periods, since their opportunity cost in downturns will be at their lowest. In other words, the opportunity cost theory predicts R&D to be countercyclical. Evidence on R&D

[1] SMEs account for over 78% of the employment and 68% of the value added of the Spanish economy (Eurostat, 2005).

investment over the cycle has been provided both at the macro level[2] and micro level.[3] In general terms, these studies show that R&D, on the contrary, behaves pro-cyclically.

Recent contributions by Aghion *et al.* (2012) and Ouyang (2011) attempt to reconcile the apparent contradiction between the empirical evidence and the predictions from the opportunity cost theory.[4] They argue that the pro cyclicality of R&D may be explained by the existence of financial constraints. As Aghion *et al.* (2012) find for a sample of French firms, in the absence of credit constraints R&D investment behaves counter cyclically, but becomes pro-cyclical as firms face sufficient credit constraints.[5]

In downturns the ability to borrow in order to innovate is reduced. Therefore, a negative demand shock will affect more R&D investments in firms that are financially constrained. This situation is even more profound among SMEs. Guellec and Wunsch-Vincent (2009) claim that in addition to the demand contraction, SMEs are faced with long delays in payment that will have a negative effect on liquidity and also with an increase in defaults and bankruptcies. These conditions may lead to a decrease in SMEs investment in R&D in recessions greater than that in large firms.

This study extends previous research by exploring the relationship between R&D and the cycle among SMEs. Specifically, we examine the extent to which negative demand shocks affect the effectiveness of R&D decisions upon total factor productivity (TFP). Our results support the hypothesis that R&D activities attenuate the negative effect of recessions on TFP. Additionally, R&D may also offer an additional source of competitive advantage in recessions as it widens the SME's TFP differential relative to non-performers. This implies that the impact of R&D upon firm's productivity has a countercyclical effect over the business cycle. We differ from

[2] See Griliches (1990), Barlevy (2004) and Comin and Gerther (2006).
[3] Barlevy (2007) and Aghion *et al.* (2012).
[4] Ouyang (2011) also claims that the observed pro-cyclicality of R&D is partly due to an aggregation bias.
[5] Similar results are found by Bonha-Padilla *et al.* (2009) and, at industry level, in Ouyang (2011).

previous studies in that we propose a two-step strategy that addresses both the potential pitfalls in estimating TFP (see e.g. Van Beveren, 2011) and the measurement of the cycle at firm level (Aghion *et al.*, 2012).

More specifically, in the first step a GMM approach is used to estimate a Cobb-Douglas production function and retrieve the TFP (Wooldridge, 2009) from a panel of Spanish manufacturing SMEs observed over the period 1990-2009. The usual empirical approach when analysing the relationship between R&D and productivity is to look at whether a productivity estimate, typically obtained as the residual of a production function, increases when firms perform R&D activities. But for such an estimate to make sense, past R&D experience should be allowed to impact future productivity. Yet some previous studies (implicitly) assume that the productivity term in the production function specification is just an idiosyncratic shock while others assume that an exogenous Markov process governs this term. It is this sort of assumptions, often critical to obtain consistent estimates (Ackerberg *et al.* 2007), what makes the analysis of the relationship between R&D and productivity to lack internal consistency. In contrast, we assume that SMEs expectation about its future productivity depends not only on their current productivity but also on lagged R&D expenditures (Doraszelski and Jaumandreu 2013, Añón Higón *et al.*, 2011).

In the second step, we use a linear regression analysis to determine the impact of the cycle and the effectiveness of R&D on TFP. Instead of using an aggregate proxy of the business cycle based on GDP (see e.g. Barlevy, 2007), we use data from the "Encuesta sobre Estrategias Empresariales" (ESEE) to gauge a measure of the cycle at firm level. In particular, each year firms report whether they operate in recessive, stationary or expansive markets. This firm's perception on the market state in which they operate provides more precise information than choosing *a priori* the recessive or expansive years. Moreover, aggregate proxies of the cycle may hide different business dynamics across industries or markets.

The rest of the article is organized as follows. Section 2 develops our main hypothesis. Section 3 presents the data and the methodology. Section 4 presents the key results. Section 5 concludes.

2. R&D activities and the business cycle. Hypothesis Development.

R&D and Productivity

An important consensus in the theoretical literature analysing the relationship between productivity and R&D activities is that these activities foster productivity growth.[6] There exist, at least, three strands of the literature supporting this positive relationship. The first strand is based on the well-known *R&D capital stock model* of Griliches (1979, 1980) that analyses the relationship between R&D investment and productivity growth (see Griliches, 2000, for a survey). In this model, the firm's stock of knowledge or knowledge capital is considered a factor of production that affects the level of firms' productivity. The second strand in the literature rendering theoretical support to the relationship between R&D and productivity growth is the *active learning model* (Ericson and Pakes, 1992, 1995, Pakes and Ericson, 1998). According to this model, firms make investment decisions knowing that their future productivity is a stochastic function of their current productivity and their current level of R&D investment. Thus, those firms that fall too far behind in the technology race leave the industry and are replaced by new entrants. R&D activities then contribute to improve firms' productivity over time. Finally*, endogenous growth theory* is the third strand of the literature

[6] The empirical literature has shown important productivity gains form R&D at macro (Coe and Helpman, 1993), industry (Bernstein, 1998; Añón Higón, 2007) and firm level (Griliches, 1980). See Hall *et al.* (2010) for a survey.

stressing the importance of R&D for productivity growth (see, e.g., Romer 1990, Aghion and Howitt, 1992).[7] This theory holds that investment in human capital, innovation or R&D, and knowledge are significant contributors to economic growth. The theory also focuses on positive externalities and spillover effects of a knowledge-based economy, which will lead to economic development. In line with the above theoretical arguments, we formulate the following hypothesis:

Hypothesis 1: SMEs performing R&D accrue higher productivity levels than SMEs that do not perform such activities.

The effectiveness of R&D over the cycle

A well-known fact is that productivity is pro-cyclical. In other words, total factor productivity (TFP) rises in booms and falls in recessions (Basu, 1996). However, SMEs may engage in certain strategic activities that may attenuate or counterbalance the negative effects of recessions upon performance. Among these strategic activities, we argue that SMEs that embrace R&D, as a core strategic policy, will be positioned for improved performance, and ultimately, survival, even in periods of decreasing demand. SMEs that conduct R&D activities may deliver new products in the market able to generate more revenues in contrast to those SMEs not conducting such activities. In addition, SMEs may conduct R&D activities aimed at process innovations, which will be effective in improving efficiency even during downturns. In line with these arguments, we formulate our second hypothesis:

[7] Moreover, R&D activities are the essence of survival since only those companies that are able to successfully innovate are able to establish and maintain a competitive advantage in the market (Audretsch and Mahmood, 1995).

Hypothesis 2: SMEs that perform R&D during recessions are able to attenuate the negative effects of the cycle on productivity vis-à-vis SMEs that do not perform such activities.

R&D over the cycle

Additionally, we argue that the impact of R&D upon firm's productivity is countercyclical over the business cycle. Downturn periods restrict R&D activities to highly productive and persistent R&D performers that are those that achieve higher returns from their R&D activities. Occasional performers and less productive firms that achieve lower returns from their R&D activities are left out of these activities. This composition effect implies that the productivity premium for R&D performers increases in downturns. In other words,

Hypothesis 3: The productivity premium of SMEs that perform R&D and that of those that do not perform is countercyclical over the business period.

3. Data and descriptive statistics.

The data used in this paper are drawn from the *Encuesta sobre Estrategias Empresariales* (ESEE, hereafter) for the period 1990–2009. This is an annual survey that is representative of Spanish manufacturing firms classified by industrial sectors and size categories. It provides exhaustive information at the firm level. As for SMEs, the sampling procedure of the ESEE excluded those firms with less than 10 employees, and firms with 10 to 200 employees were randomly sampled, holding around 5% of the population in 1990. Important efforts have been made to minimise attrition and to annually incorporate new firms with the same sampling criteria as in the base year, so that the sample of firms remains representative of the Spanish manufacturing SMEs over time.[8]

We have a sample of 50,390 observations corresponding to 3,624 SMEs. From this sample, in order to estimate TFP and to analyse the impact of R&D strategies on TFP, we sample out those SMEs that fail to supply relevant information in any given year. Further as our TFP estimation method requires that SMEs supply information for at least three consecutive years, we remove all SMEs that do not accomplish this criterion. After cleansing the data we end up with a sample of 15,810 observations corresponding to 1,105 SMEs.[9]

The two variables of interest in this work (perception on the demand evolution in the SME's main market and R&D status) are obtained from the following two questions of the survey. The question we use to construct the firm level indicator of the market/cycle is: "Indicate whether the evolution of the firm main market has been expansive, stable or recessive". As we are interested in analysing the effect of recessions we group the expansive and stable categories and compare it to the recessive one. This variable is quite useful for testing the effectiveness of R&D in recessive periods as firms' answers provide more precise information than choosing *a priori* which were the recessive or expansive years. As for the firm R&D status the relevant question is: "Indicate if during this year the firm has undertaken or contracted any R&D activity and the expenses on those activities".

In Figure 1 we plot the evolution between 1990-2009 of our firm measure of the cycle, namely the percentage of SMEs that declare that its main market is recessive, and

[8] See http://www.fundacionsepi.es/esee/sp/pesentacion.asp for further details.
[9] We do not use any observation for 1990, as we cannot compute productivity for this year in this survey.

the rate of growth of the GDP as a macroeconomic measure of the economic cycle. In general terms, the evolution of our firm level indicator is quite similar to that of the GDP: when the rate of growth of GDP increases, the percentage of firms that declare that its main market is in recession decreases and vice versa. This is especially evident in the crisis episodes at the beginning of 1990s and 2000s, and with the start of the current economic crisis in 2007. Escrivano and Strucchi (2008), using the same data set for a shorter period, point that these answers on the timing of the business cycle, based on firms' perceptions, are consistent with the timing of the business cycle defined in terms of growth rates of GDP. From this, they conclude that the consistency of the dating of recessions and expansions periods using information at different aggregation levels supports the use of the ESEE surveys to analyse the firms' productivity catching up through the business cycle.[10] We also find that SMEs' answers in our sample on the state of their markets are in general consistent with the growth rate of the economy as measured by the GDP. In our empirical study we rather use the firm level proxy of the cycle than the aggregate measure. This firm's perception on the market state in which they operate provides more information than choosing *a priori* the recessive or expansive years. Moreover, aggregate proxies of the cycle may hide different business dynamics across industries or markets.

Figure 2 plots both the proportion of SMEs that undertake R&D activities and the proportion of SMEs that declare that their main market is in recession (our firm level indicator of the economic cycle). The percentage of firms undertaking R&D shows an increasing trend along the 20 years of the sample (from 17.93 in 1990 to 23.04% in 2009). However, this increasing trend hides some cyclical movements that, in general,

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[10] Klepper (1997) in a related but different approach makes a similar point: the firms' perception of the market might capture the way many industries evolve.

follow the evolution of our firm level indicator of the cycle except for the last recession period (from year 2007 onwards) in which the proportion of firms performing R&D maintains its increasing trend.

Although, we do not aim to analyse the relationship between the extensive margin of R&D and the cycle, we present a descriptive statistic on this relationship by estimating the following *probit* equation:

$$d_{RD,it} = \beta_0 + \beta_1 d_{C,\,it} + \sum_{j=1}^{10} \gamma_j ind_{ij} + \sum_{t=1991}^{2009} \lambda_t year_{it} + e_{it} \qquad (1)$$

where the dependent variable $d_{RD,it}$ is a dummy variable that takes value 1 if firm i performs R&D in t and 0 otherwise and $d_{C,it}$ is a dummy variable that takes value 1 if the firm main market is in recession and 0 otherwise. We also include a set of year and industry dummies. The results of these regressions, shown in Table 1, suggest that those firms that declare that their main market is in recession have a significant 5.5% lower probability of performing R&D. This result provides evidence in favour of a pro-cyclical behaviour of the extensive margin of R&D.[11]

[Table 1 around here]

Next we identify some stylized facts about firms performing and non-performing R&D using a simple regression analysis (see Table 2). The objective of this analysis is to explore the relationship between firm R&D status and some basic firm characteristics. In particular, we estimate equations of the form:

$$\log\left(y_{it}\right) = \beta_0 + \beta_1 RD_{it} + \delta \log(size_{it}) + \sum_{j=1}^{10} \gamma_j ind_{ij} + \sum_{t=1991}^{2009} \lambda_t year_{it} + e_{it} \qquad (2)$$

[11] This result should be taken with caution as financial constraints are an important determinant of the relationship between R&D and the cycle, see Aghion *et al.* (2013), and in this regression we do not take into account whether firms are credit constrained.

where the dependent variable, y_{it}, is alternatively output, capital and intermediate materials per worker and size (as measured by the number of employees). The variable RD_{it} is a dummy variable that takes value one if the firm undertakes R&D activities and zero otherwise. We also control for the size of the firm (measured by the number of workers), and for industries and years.

[Table 2 around here]

The differences (in %) between R&D performers and non-performers, for each of the five considered firm characteristics, computed from the estimated coefficient $\beta_1$as 100(exp(β_1) − 1), show that R&D performers are significantly bigger, more capital and intermediate materials intensive and have larger labour productivity (sales per worker) than non-performers. Consequently, it seems important to acknowledge the significant differences between firms engaged or not in R&D when estimating productivity.[12] We do this by considering that R&D performers have a different demand function for intermediate materials than non-performers.

4. Production function and TFP estimation.

To obtain the production function estimates, we assume that firms produce using a Cobb-Douglas technology:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + \omega_{it} + \eta_{it} \qquad (3)$$

where y_{it} is the natural log of production of firm i at time t, l_{it} is the natural log of labour, k_{it} is the natural log of capital, m_{it} is the natural log of intermediate materials,

[12] As pointed out by De Loecker (2007, 2010) for exporting, this might be an important refinement in the analysis of the effects of performing R&D on productivity.

and μ_t are time effects. As for the unobservables, ω_{it} is the productivity (not observed by the econometrician but observable or predictable by firms) and η_{it} is a standard *i.i.d.* error term that is neither observed nor predictable by the firm.

It is also assumed that capital evolves following a certain law of motion that is not directly related to current productivity shocks (i.e., it is a state variable), whereas labour and intermediate materials are inputs that can be adjusted whenever the firm faces a productivity shock (i.e. they are variable factors).[13]

Under these assumptions, Olley and Pakes (1996, hereafter OP) show how to obtain consistent estimates of the production function coefficients using a semiparametric procedure; see also Levinshon and Petrin, (2003, hereafter LP), for a closely related estimation strategy. However, here we follow Wooldridge (2009), who argues that both OP and LP's estimation methods can be reconsidered as consisting of two equations which can be jointly estimated by GMM: the first equation tackles the problem of endogeneity of the non-dynamic inputs (that is, the variable factors); and, the second equation deals with the issue of the law of motion of productivity. Next we consider each in detail.

Let us start considering first the problem of endogeneity of the non-dynamic inputs. Correlation between labour and intermediate inputs with productivity complicates the estimation of equation (3), because it makes the OLS estimator biased and the fixed-effects and instrumental variables methods generally unreliable (Ackerberg *et al.*, 2006). Both OP and LP's methods use a control function approach to

[13] The law of motion for capital follows a deterministic dynamic process according to which $k_{it} = (1-\delta)k_{it-1} + I_{it-1}$. Thus, it is assumed that the capital the firm uses in period *t* was actually decided in period *t-1* (it takes a full production period for the capital to be ordered, received and installed by the firm before it becomes operative). Labour and materials (unlike capital) are chosen in period *t*, the period they actually get used (and, therefore, they can be a function of ω_{it}). These timing assumptions make them non-dynamic inputs, in the sense that (and again unlike capital) current choices for them have no impact on future choices.

solve this problem, by using investment in capital and materials, respectively, to proxy for “unobserved” firm productivity.

In particular, the OP’s method assumes that the demand for investment in capital, $i_{it} = i\left(k_{it}, \omega_{it}\right)$, is a function of firms’ capital and productivity. To circumvent the problem of firms with zero investment in capital, the LP’s method uses the demand for materials (intermediate inputs), $m_{it} = m\left(k_{it}, \omega_{it}\right)$, instead, as a proxy variable to recover “unobserved” firm’s productivity. Since we follow this last approach, we concentrate on the demand of materials hereafter.[14]

Therefore, when estimating productivity using these general versions of OP and LP in a sample where some firms do not perform R&D, while others do, it is assumed that the demand of intermediate materials for the different types of firms according to their R&D statuses is identical. However, heterogeneity in these firms’ R&D strategies may influence the demand of intermediate inputs. Therefore, analogously to De Loecker (2007, 2010) or Manjon *et al.* (2013), when analysing the effects of exporting on firms’ productivity, we consider different demands of intermediate materials for R&D and non-R&D firms (i.e. firms that perform and do not perform R&D respectively). Thus, we write the demand of materials as:

$$m_{it} = m_{R\&D}\left(k_{it}, \omega_{it}\right) \tag{4}$$

where we include the subscript *R&D* to denote different demands of intermediate inputs for R&D and non-R&D firms. Since the demand of intermediate materials is assumed to be monotonic in productivity, it can be inverted to generate the following inverse demand function for materials:

[14] Both the investment of capital demand function and the demand for intermediate materials are assumed to be strictly increasing in ω_{it} (in the case of the investment of capital this is assumed in the region in which i_{it}>0). That is, conditional on k_{it}, a firm with higher ω_{it} optimally invests more (or demands more materials).

$$\omega_{it} = h_{R\&D}\left(k_{it}, m_{it}\right) \quad (5)$$

where $h_{R\&D}$ is an unknown function of k_{it} and m_{it}. Then, substituting expression (4) into the production function (3) we get:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + h_{R\&D}\left(k_{it}, m_{it}\right) + \eta_{it} \quad (6)$$

Finally, by explicitly considering different demand of intermediate materials for R&D and non-R&D firms, our first estimation equation for the production function is:

$$y_{it} = \beta_l l_{it} + \mu_t + 1(R\&D_{it-1}{=}0)H_{NP}\left(k_{it}, m_{it}\right) + 1(R\&D_{it-1}{=}1)H_{R\&D}\left(k_{it}, m_{it}\right) + \eta_{it} \quad (7)$$

where $1(RD_{it\text{-}1}= 0)$ and $1(RD_{it\text{-}1}= 1)$ are indicator functions that take value one for non-R&D performing firms and R&D performing firms, respectively. Further, the unknown functions H in (7) are proxied by second-degree polynomials in their respective arguments.

With the specification in equation (7), the difference in the inverse demand function between R&D and non-R&D firms arises not only from differences in the coefficients of k_{it} and m_{it} but also by the fact that the inverse demand function of R&D firms includes an R&D dummy. This is not equivalent to introduce an R&D dummy as additional input in the production function, as the R&D dummy is interacted with all the terms k_{it} and m_{it} in its corresponding polynomial. For example, introducing an R&D only dummy as an input in the production function will cause at least two problems. First, an identification problem, as we will need another estimation step to identify the parameter associated to that variable. Second, implies that a firm can substitute any input with R&D performance at constant unit elasticity (see De Loecker, 2007, 2010, for similar arguments applied to export dummies).

Notice, however, that we cannot identify β_k *and* β_m from (7). This is achieved by the inclusion of a second estimation equation in the GMM-system that deals with the law of motion for productivity.

The standard OP/LP's approaches consider that productivity evolves according to an exogenous Markov process:

$$\omega_{it} = E\left[\omega_{it}\right] + \xi_{it} = f\left(\omega_{it-1}\right) + \xi_{it} \tag{8}$$

where f is an unknown function that relates productivity in t with productivity in t-1 and ξ_{it} is an innovation term uncorrelated by definition with k_{it}. However, this assumption neglects the possibility of R&D experience to affect productivity. Consequently, here we consider a more general (endogenous Markov) process in which previous R&D history can influence the dynamics of productivity:

$$\omega_{it} = E\left[\omega_{it} \middle| \omega_{it-1}, R\&D_{it-1}\right] + \xi_{it} = f\left(\omega_{it-1}, R\&D_{it-1}\right) + \xi_{it} \tag{9}$$

where $R\&D_{\text{it-1}}$ indicates whether the firm, in period *t-1*, performs or not R&D. Obviously, the reference category is not performing R&D.

Let us now rewrite the production function in (2) using (8) as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t + f\left(\omega_{it-1}, R\&D_{it-1}\right) + \xi_{it} + \eta_{it} \tag{10}$$

Further, since $\omega_{it} = h_{R\&D}\left(k_{it}, m_{it}\right)$, we can rewrite $f\left(\omega_{it-1}, R\&D_{it-1}\right)$ as:

$$\begin{aligned} f\left(\omega_{it-1}, R\&D_{it-1}\right) &= f\left[h_{R\&D}\left(k_{it-1}, m_{it-1}\right), R\&D_{it-1}\right] \\ &= F_{R\&D}\left(k_{it-1}, m_{it-1}, R\&D_{it-1}\right) \\ &= 1(R\&D_{it-1}{=}0)F_{NP}\left(k_{it-1}, m_{it-1}\right) + 1(R\&D_{it-1}{=}1)F_{R\&D}\left(k_{it-1}, m_{it-1}, R\&D_{it-1}\right) \end{aligned} \tag{11}$$

with F being unknown functions to be proxied by second degree polynomials in their respective arguments. As above, an R&D dummy is used to define the polynomials and is also included as an additional dummy in the polynomials corresponding to R&D firms.

Lastly, substituting (11) into (10), our second estimation equation for the production function is given by:

$$\begin{aligned} y_{it} = \beta_0 &+ \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \mu_t \\ &+ 1(NP)F_{NP}\left(k_{it-1}, m_{it-1}\right) + 1(R\&D)F_{R\&D}\left(k_{it-1}, m_{it-1}\right) + u_{it} \end{aligned} \tag{12}$$

where $u_{it}=\xi_{it}+\eta_{it}$ is a composed error term.

Wooldridge (2009) proposes to estimate jointly the system of equations (7) and (12) by GMM using the appropriate instruments and moment conditions for each equation. Ackerberg *et al.* (2006) showed that there exists an identification problem with a first step estimation of variable inputs coefficients (affecting the labour input) in previous methods relying on a two-step estimation procedure (OP and LP), and derived a mixture of OP and LP's approaches to solve the problem. However, theirs is still a two-step estimation procedure. More recently, Wooldridge (2009) has argued that both OP and LP's estimation methods can be reconsidered as consisting of two equations which can be jointly estimated by GMM in a one-step procedure. This joint estimation strategy has the advantages of increasing efficiency relatively to two-step procedures, making unnecessary bootstrapping for the calculus of standard errors, and also solving the aforementioned identification problem.

5. Results

In the first step of our analysis, using the methodology explained above, we estimate the production function (2) for each of our 10 industries to obtain estimates of TFP.[15] Using these estimates, we calculate the (log) of TFP for firm *i* at time *t* for industry *s*, denoted tfp_{it}^{s}, as:

$$tfp_{it}^{s} = y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - \mu_{it} \tag{13}$$

where *s*is an industry indicator, and *i* and *t* refer to firm and time, respectively. It is important to note that including a vector of time dummies (μ_{it}) in the TFP estimation

[15] Following Doraszelski and Jaumandreu (2013) we group the 20 industries in which the ESEE classifies firms into 10 industries. The aim is to get enough observations to carry out industry-by-industry estimations. The coefficients estimated at industry level are reported in Table A.1 in the Appendix.

makes our estimated TFP time effects free. Controlling for time effects is essential as we are interested in disentangling the effects of the macroeconomic cycle (mainly captured by the time dummies) from those stemming from the market conditions faced by individual firms.

In the second step, we pool TFP estimates for all industries and estimate a reduced form equation that has these TFP estimates as dependent variable and R&D status and our firm level cycle proxy as covariates.

Thus, our estimation equation is:

$$tfp^{s}_{it} = \beta_0 + \beta_1 d_{C,it} + \beta_2 d_{R\&D,it-2} + \beta_3 d_{C,it-2} \cdot d_{R\&D,it-2} + \beta_4 size_{it} + \sum_{j=1}^{10} \gamma_j ind_{ij} + u_{it} \qquad (14)$$

where $d_{C,it}$ is a dummy variable (capturing the cycle at firm level) that takes value 1 if the firm declares that in year *t-2* its main market is in recession and 0 otherwise; $d_{R\&D,it-2}$ is a dummy variable that takes value 1 if the firm performs R&D in period *t*-2;[16] and, finally $d_{C,it-2} \cdot d_{R\&D,it-2}$ is an interactive dummy that results from multiplying the recessive demand and R&D dummies (thus, it takes value 1 for firms performing R&D that declare that their main market is in recession). Further, we include a set industry dummies to control for industry specific shocks and the log of the number of workers to control for the (log) size of the firm.

In equation (14), β_0 is by construction the average productivity of non-R&D firms in expansive periods; and, β_0+β_1 is the average productivity of non-R&D firms in recessive periods. Analogously, β_0+β_2 and β_0+β_1+β_2+β_3 are the average productivities of R&D firms in expansive and recessive periods, respectively.

[16] We lag this variable 2 periods to avoid potential endogeneity problems. Our main conclusions largely hold, however, if we use a dummy variable that takes value 1 if the firm performs R&D in period *t*-1 (rather than in period *t*-2). This is also the case if we use a dummy variable that takes the value 1 if the firm declares that in year *t*-1 (rather than in period *t*) its main market was in recession.

Therefore, from the above productivity levels we obtain that β_2 and $\beta_2+\beta_3$ are the average TFP differences (TFP premium of R&D firms) between R&D and non-R&D firms in expansive and recessive periods, respectively. According to Hypothesis 1, we expect both of them to be positive. Further, the average effect of recessions on the TFP of non-R&D firms is given by β_1, and analogously the average effect of recessions on the TFP of R&D firms is measured by $\beta_1+\beta_3$. Therefore, verification of Hypothesis 2 implies testing whether β_3 is positive, i.e. whether performing R&D attenuates the negative effects of recessions on TFP.

As the dependent variable is the log of TFP, each of the TFP differences (in %) described above are computed from the corresponding estimated coefficient, or sum of the coefficients, as 100(exp(β) - 1). These differences, shown in Table 3, confirm our Hypothesis 1: the TFP premium of R&D firms is 3.14% in expansive periods and more than double (7.40%) in recessive periods. This higher TFP premium of R&D firms in recessive periods results from the different effect of recessions in non-R&D and R&D SMEs: whereas the TFP of non-R&D SMEs decreases 3.7% in downturn, the TFP of R&D SMEs is not affected (the estimate of $\beta_1+\beta_3$ is not significant at any conventional level). This result goes in line with our Hypothesis 2 that posed that performing R&D attenuates the effects of the cycle. Further, the estimate β_3 (that measures the difference between the R&D productivity premia in recessions and expansions) is positive and significant confirming the countercyclical effect of R&D on productivity (Hypothesis 3).

All in all, our results confirm both that performing R&D has important rewards in terms of productivity (Hypothesis 1) for SMEs and provide evidence on our main hypotheses (Hypothesis 2 and 3), namely that performing R&D contributes to attenuate (in our case to completely offset) the negative effects of the cycle on firm productivity, and the countercyclical effect of performing R&D. In addition, the results in Table 3 show a high degree of heterogeneity across industries in terms of productivity and that TFP is pro-cyclical, i.e., in periods of recession the average productivity of SMEs decreases. Finally, the results imply a positive relationship between size and TFP, as found in previous studies.

6. Conclusions

Embracing R&D and innovation activities is particularly relevant for SMEs, as these strategies are crucial to productivity growth, firm's competitiveness and ultimately their survival. While firms that conduct R&D activities are able to bring new products to the market and improve efficiency through new processes, firms that do not embrace R&D activities are more exposed to fluctuation in demand. Though the availability of resources to invest in R&D decreases in recessions, particularly in the case of SMEs, their commitment to these activities is essential to remain competitive and to counteract the effects of the cycle. We test this tenet in a panel of Spanish SMEs observed over practically two decades. Our findings show that R&D activities contribute to improve productivity performance in SMEs. Firms conducting R&D are more productive than non-R&D SMEs. Also, TFP behaves pro-cyclically; i.e. increases in booms but decreases in recessive periods. However, SMEs embracing R&D are able to offset this negative effect on their performance. Lastly, our results show that R&D increases the TFP premium in periods of contraction. More precisely, we find that the productivity gap between SMEs conducting vs. non-conducting R&D activities almost doubles in downturns. This implies that the impact of R&D upon firm's productivity is countercyclical over the business cycle.

The results of this study have important management and policy implications.

Our results show that the positive effect of conducting R&D upon performance is not just limited to expansive periods. This finding reveals the importance of devoting efforts to R&D as a core management strategy over the cycle. SMEs implementing R&D and innovating activities are better positioned to bring new products into the markets, which may be able to contribute to increase revenues (Shefer and Frenkel, 2005); or to introduce new process, which may report them gains in efficiency and competitiveness. Nevertheless, not all SMEs are able to acquire the resources to conduct R&D activities in recessions. It has been argued that SMEs are faced with credit constraints in recessions, which may impede to undertake R&D activities (Guellec and Wunsch-Vincent, 2009). It is for this kind of arguments that government policy should be focused on providing the incentives to invest in and to commit to R&D activities over the long term, particularly to SMEs. Examples of instruments to encourage investment in R&D may go from tax credits or subsidies to R&D to the promotion of collaborations with other firms or universities and research institutions.

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Appendix.

Table A.1. Production function estimates (by industry).

	Labour		Intermediate materials		Capital	
Industry	$\boldsymbol{\beta_l}$	**s.e.**	$\boldsymbol{\beta_m}$	**s.e.**	$\boldsymbol{\beta_k}$	**s.e**
1. Metals and metal products	0.280***	(0.009)	0.585***	(0.080)	0.058***	(0.022)
2. Non-metallic minerals	0.263***	(0.009)	0.492***	(0.058)	0.035	(0.032)
3. Chemical products	0.136***	(0.010)	0.754***	(0.145)	0.072**	(0.033)
4. Agric. and ind. machinery	0.268***	(0.012)	0.632***	(0.074)	0.000	(0.021)
5. Office, data processing machines and electrical goods	0.359***	(0.014)	0.677***	(0.084)	0.053*	(0.029)
6. Transport equipment	0.274***	(0.014)	0.765***	(0.112)	0.026	(0.033)
7. Food, drink and tobacco	0.164***	(0.007)	0.776***	(0.083)	0.052**	(0.023)
8. Textile, leather and shoes	0.338***	(0.009)	0.459***	(0.019)	0.063***	(0.019)
9. Timber and furniture	0.315***	(0.009)	0.585***	(0.068)	0.034**	(0.016)
10. Paper and printing products	0.272***	(0.010)	0.658***	(0.102)	0.055***	(0.019

Notes:

1. Robust standard errors in parenthesis. Significance level: ***p<1%, **p<5% and * p<10%.
2. The production function estimates control for year dummies.

Figure 1. Percentage of firms in recession and rate of growth of the GDP (%)

Figure 2. Percentage of firms that perform R&D and percentage of firms in recession each year.

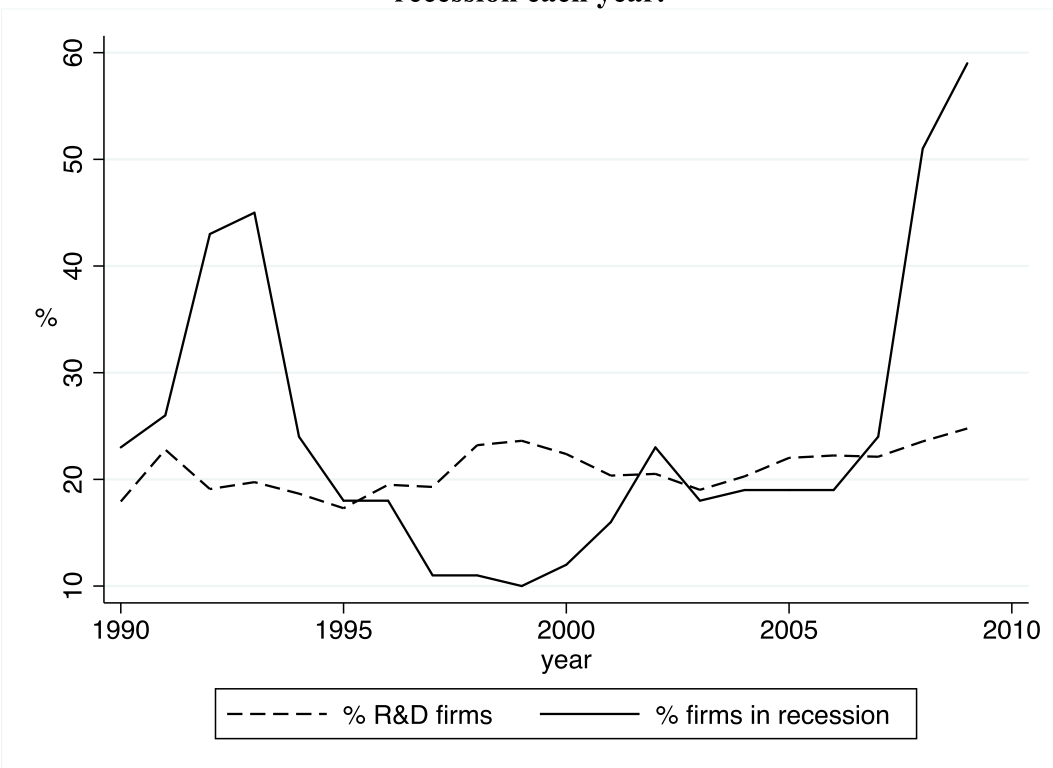

Table 1. The effect of the cycle on the probability of performing R&D.

	Marginal effect	s.e.
$d_{C,it}$	-0.055*	0.003
Number of observations	15,810	
Pseudo R^2	0.085	

Notes:

1. * mean significance at the 10% level.
2. The regression includes year and industry dummies.

Table 2. Differences across SMEs performing and non performing R&D.

	Difference	s.e.
Sales per worker	35.967***	0.015
Capital per worker	49.058***	0.023
Materials per worker	49.927***	0.021
Size	104.587***	0.018

Notes:

1. *** mean significance at the 1% level.
2. All regressions include year and industry dummies.

Table 3: Impact of the cycle and R&D strategies on TFP.

	TFP
Constant	4.237***
	(0.012)
$d_{C,it}$	-0.037***
	(0.008)
$d_{R\&D,it-1}$	0.031***
	(0.006)
$d_{C,it} \cdot d_{R\&D,it-1}$	0.041**
	(0.015)
$size_{it}$	0.084***
	(0.003)
Sectors	
Non-metallic minerals	1.666***
	(0.012)
Chemical products	-2.182***
	(0.009)
Agricultural and industrial machinery	0.231***
	(0.010)
Office, data processing machines and electrical goods	-1.520***
	(0.011)
Transport equipment	-2.345***
	(0.014)
Food drink and tobacco	-2.268***
	(0.008)
Textile leather and shoes	1.394***
	(0.010)
Timber and furniture	0.142***
	(0.008)
Paper and printing products	-1.020***
	(0.009)
Number of observations	11,642
R^2	0.967

Table 4. Differences in TFP.

	% change	*p*-value
Differences in productivity between R&D and non R&D firms in expansions.	3.136	0.000
Differences in productivity between R&D and non R&D firms in recessions	7.397	0.000
Effect of recession phases on TFP for non-R&D firms	-3.653	0.000
Effect of recession phases on TFP for R&D firms	0.327	0.801