Estudios de Economía Aplicada

Vol. 37-3 2019 pp. 186-200

INNOVATION AND PERFORMANCE: THE CONTRIBUTION OF INVESTMENTS IN R&D TO FIRM PROFITABILITY ACCORDING TO THE TECHNOLOGICAL FRONTIER

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Recibido: 9 de Mayo de 2019
Aceptado: 6 de Julio de 2019

ABSTRACT

This study analyses the influence of innovative efforts, measured by R&D investments, on the financial performance of firms, considering its position in relation to the technological frontier. Recent researches, especially Aghion & Howitt, 2009; Aghion, Akcigit, & Howitt, 2013, have demonstrated that the firm's technological position has a strong impact on the results of the applied investment, since the structure of incentives and potential opportunity costs influence the relation between the variables. For this purpose, the present study uses the frontier analysis with order-α partial frontiers, aiming to capture fluctuations of proximity to the border and its influence on the relation "R & D investment versus performance". Such approach allows different frontiers to be estimated for different quantiles, which provides a more consistent estimate of efficiency scores, which become more robust in relation to traditional problems of outliers and dimensionality. The sample of this article was made up of 2.000 firms and the data needed for the survey was extracted from the European Commission, a database covering 40 sectors in 46 countries. The results of the model suggest that the more efficient firms or the ones situated on the efficiency frontier achieve more profits from the same level of R&D investment compared with less efficient firms. This influence of proximity to the frontier emphasizes that the most efficient firms use the investments in R&D in order to obtain greater returns, what can explain that innovation is not shown uniform among firms.

Keywords: firm's performance; innovation; efficiency.

RESUMEN

Este estudio analiza la influencia de los esfuerzos innovadores, medidos por las inversiones en I&D, en el desempeño financiero de las empresas, considerando su posición en relación con la frontera tecnológica. Investigaciones recientes, especialmente Aghion & Howitt, 2009; Aghion, Akcigit y Howitt, 2013, han demostrado que la posición tecnológica de la empresa tiene un fuerte impacto en los resultados de la inversión aplicada, ya que la estructura de incentivos y los costos de oportunidad potenciales influyen en la relación entre las variables. Para este propósito, el presente estudio utiliza el análisis de la frontera con las fronteras parciales de orden-α. Este enfoque permite estimar diferentes fronteras para diferentes cuantiles, lo que proporciona una estimación más consistente de las puntuaciones de eficiencia, que se vuelven más sólidas en relación con los problemas tradicionales de valores atípicos y dimensionalidad. La muestra de este artículo estaba compuesta por 2.000 empresas y los datos necesarios para la encuesta se extrajeron de la Comisión Europea, una base de datos que abarca 40 sectores en 46 países. Los resultados del modelo sugieren que las empresas más eficientes, las situadas en la frontera de la eficiencia, logran más ganancias del mismo nivel de inversión en I&D en comparación con las empresas menos eficientes. Esta influencia de la proximidad a la frontera muestra que las empresas más eficientes utilizan las inversiones en P&D para obtener rendimientos más altos, lo que puede explicar que la innovación no sea uniforme entre las empresas.

Palabras clave: desempeño de la firma; innovación; eficiencia.

Clasificación JEL: L25; O30; O32.

1. INTRODUCTION

This study aims to analyze how the efforts in innovation contribute to the performance of companies, considering its heterogeneous effect. Based on the theoretical and empirical findings, we can derive three testable hypotheses: (i) the financial performance of firms, through profits, is positively linked to investments in R&D and innovation; (ii) this positive relation is heterogeneous and is related to the firm's technological position (efficiency degree); (iii) different efficiency standards imply different opportunity costs, which have an impact on the 'investments versus performance' relation. The highlighted hypotheses indicate that firms, located near or far from the frontier, or even efficient in different patterns of dominance in the sample (efficient firms according to the position of the partial frontier), enjoy heterogeneous effects of investments in innovation.

Investments in innovation have been, over the last decades, increasingly important for the growth and performance of firms around the world, both in terms of products and processes. Innovation, especially in a globalized and competitive economy, is a fundamental strategy for firm survival. However, the causal relation between financial performance and investment in research and development (R&D) is still controversial, while its returns are not always positive, having a high degree of uncertainty. Analyzing this relation in terms of the technological or efficient frontier concept, we can observe that even though firms could invest the same amount of money in R&D, the rewards are quite different from one firm to another (Aghion, García-Peñalosa, & Howitt, 2004; Hall, 2002; Hall, Lotti, & Mairesse, 2013). In this sense, the concept of the efficient frontier can be the key to shedding light on this issue.

The efficient frontier is defined as the range of the best possible firm performance, given existing production techniques. A firm operating on its technological frontier can only improve its performance when it is able to promote a change in the limits of its technological frontier as a direct result of innovation. On the other hand, efforts to move the frontier limits require significant financial investment, which also represents an expressive opportunity cost associated with risk of failure, especially when we compare firms operating in the "neighborhood" of the technological frontier and those most distant from this frontier (Aghion & Howitt, 2009; Aghion, Akcigit, & Howitt, 2013). Coad and Rao (2006) (and in more recent researches, Coad (2008; 2011)) showed empirical evidence of this relation, finding that investments in innovation were more valuable for market leading firms than for market followers. However, this needs to be further investigated, particularly around the issue of profitability associated with investment in innovation.

Until now, the metrics used to measure "distance to the frontier" have consisted of quantile regressions, where the highest quantiles are associated with the higher mean innovation indicators. This higher average is attributed to an increased intensity in innovative activities, being defined as the "technological frontier" (Coad, 2011).

However, the measurement of the frontier, and consequently the distance of firms in relation to this frontier, is not easy. The current linear regression techniques fail to capture important characteristics of technologically efficient production. The structure of efficient production at the frontier can be distinguished from an average production structure by a data sample. A “best practice” does not necessarily apply in an “average practice” as it does not incorporate aspects of economies of scale and scope (Daraio & Simar, 2007).

This study used a different technique of data envelopment analysis with partial frontiers, namely order-α partial frontier. In the traditional method of frontier analysis, the frontier for efficient firms was estimated based on a set of products and inputs. However, in the standard technique, problems associated with extreme values (outliers) and restrictions of dimensionality made the estimated scores tendentious and highly sensitive to variations in the sample. In the order-α partial approach, different boundaries are estimated for different quantiles. This technique allows a more consistent and robust estimation of efficiency scores, so that the extreme values are treated as super-efficient units rather than the ultimate frontier (Daraio & Simar, 2007; Simar & Wilson, 2013). After the calculation of efficiency scores, an estimation was performed by linear regression on a sample of 2000 firms. The data for the model estimation were taken from the European Commission report (2013), which covered 40 sectors in 46 countries.

In this way, we highlight recent researches, as enumerate below:

1) Unlike Coad (2011), measuring the position of firms in relation to the technological frontier, through the technique of efficiency scores, makes it possible to capture relevant aspects of the technological position that are not properly treated from the average effect of the sample (Daraio & Simar, 2007);
2) The technique of partial frontier, besides being the most robust in the efficiency analysis, allows a more precise analysis regarding the quantile regression technique, especially when considering different efficiency standards in the sample (efficient firms in different sample quantiles) (Simar & Wilson, 2013);
3) Analyzing these effects from the top innovation investor sample allows a better understanding of the relation between the variables, without incurring on defects associated with sample selection problems (Greene, 2012).

The results show that: (1) efficient firms present higher returns on R&D investments in relation to less efficient firms; (2) efficient firms located in lower quantis of the partial frontier have a smaller effect of return on investments, when compared to efficient firms at the final frontier. These results are consistent with the literature on endogenous growth, especially Acghoglu, Aghion and Howitt (2006), Aghion and Howitt (2009) and Aghion, Akcigit and Howitt (2013).

Thus, this study is relevant in its use of a different technique for the estimation of the efficiency of frontiers, and in its discussion of the controversial relation between financial performance and investment in R&D based on identified efficiency scores.

This paper is structured as follows: (1) the introduction, with the description of the study and the relevance of the theme; (2) the theoretical and empirical referential, presented the main studies that support the presented model and the findings of the research; (3) empirical methodology, highlighting the technique employed to estimate the model; (4) analysis of the results, presenting the results of the estimates obtained in the model; (5) discussion with recent research, synthesizing the main findings and confronting empirical studies on the subject; (6) robustness of the research, describing the inference power of the study and its limitations as a suggestion for future researches, and finally; (7) the final considerations, summarizing the main findings of the research.

2. THEORETICAL AND EMPIRICAL BACKGROUND

Schumpeter (1961) shows that technological innovation can be defined as the implementation of new products or processes, or significant changes to existing products or processes. It is expected that the innovation process requires firms to invest in R&D. Investment in R&D has been linked to innovation (Acemoglu, Aghion, & Zilibotti, 2006), since this type of investment is considered one of the classic innovative activities (Andreassi & Sbragia, 2002). Thus, the innovation process can be understood from the science and technology development process, with results achieved largely by significant R&D activity (Grupp, 1998).

According to the manual of the Organization for Economic Cooperation and Development (OECD; quoted in Jensen et al., 2004), R&D activity comprises creative work undertaken on a systematic basis to increase a stock of knowledge, including scientific and technological knowledge, as well as the use of this knowledge for new applications. In this way, the term R&D covers three activities: i) Basic Research: Experimental or theoretical work in order to understand observable phenomena and facts, but without a particular application; ii) Applied Research: Original research in order to acquire new knowledge directed at a practical purpose; iii) Experimental Development: Application of existing knowledge in order to develop new materials, products, processes, systems, and services, or the improvement of existing ones.

However, investment in R&D cannot be regarded as risk free and requires significant opportunity costs. Based on the classic potential surprise of Shackle (1953), we can arguee that businesses investing in innovation have several predicted hypotheses, and non-impossible ones, superior to the conventional number in the activity of expanding existing capital stock. Therefore, financing related to R&D activities becomes scarce due to higher risks for entrepreneurs (borrowers) and bankers (lenders). As argue Teece (2009), high R&D investments will not necessarily mean performance gains. According the author, "the business enterprise must do a lot more than simply allocate large expenditures to R&D" (Teece, 2009, p.203).

In this way, Pavitt (2005) argue that:

> The process of innovation is complex, involving many variables whose proprieties and interactions (and economic usefulness) are understood imperfectly. As a consequence, firms are not able to explain fully and predict accurately either the technical performance of major innovations, or their acceptability to potential users (or in some cases even who the potential users are) (Pavitt, 2005, p.100).

From this perspective, the entrepreneur who invests in R&D also has to make complex decisions because different types of research investments can cover from basic to applied research. Basic research can be distinguished from applied research in that the former focuses on the advancement of fundamental knowledge, opening new fields of scientific activity, where the latter focuses on the basic research already conducted, seeking to develop practical applications for the research. Investment in basic research, therefore, involves a higher degree of uncertainty than investment in applied research. As we move from basic to applied research within the R&D spectrum, the uncertainty in the decision to invest lessens (Arrow & Hurwicz, 1972).

To analyze R&D funding, Minsky (1975) estimated that a borrower's risk is present because the potential investor believes that his future debts are fixed while the prospective revenue stream is uncertain. The weights used for the risk of the investment are even more significant since the relation between the R&D investment and profitability is still controversial. Morbey (1989) analyzed 800 firms between 1976 and 1985 and found that there was a strong positive correlation between spending on R&D and sales for firms operating in specific sectors. However, firms that had higher profitability did not necessarily increase their spending on R&D in relation to revenue. Although every investment in R&D is surrounded by uncertainty regarding the desired return, we can see that innovation, when successful, provides significant financial returns. It can be verified in the studies conducted by Wang (2007) and Hirschey (2003), when it was identified positive relationships between the return on invested capital and variables such as profit margin, cash flow, and market value.

In Brazil, Andreassi and Sbragia (2002) sought to understand the relationship between the innovation effort and a set of profitability indicators, such as market share and revenues, generated by new or improved products. The results showed that the investments in R&D were strongly associated with the future role of new products in total revenue at the firms, and that, unlike what happens in other countries, the sales results seemed to constrain R&D investment in the future.

2.1. The Concept of "Distance of Frontier"

An important concept regarding innovation activities is related to the distance to the technological frontier. Leading firms generally operate on the edge of the technological frontier of their industries and can only improve their performance when they are able to move the technological frontier through innovation (Coad, 2008; Coad & Rao, 2006). In addition, these firms have the financial resources needed to fund innovative efforts. The firms that operate far from the technological frontier and are considered market "followers" may get better performance by using existing technologies, hence saving R&D financial resources.

However, firms located further away from the technological frontier should maintain some level of R&D investments. This is justified because, as Cohen and Levinthal (1990) show, follower firms must be able to understand the knowledge developed by leaders. A firm with a low level of internal knowledge would hardly be able to recognize and assimilate the knowledges flowing in its external environment. Thus, R&D investment would be a mechanism not only to develop internal knowledge and promote present innovation, but also to increase the firm's absorptive capacity, making possible the adhesion to new technologies.

Thus, investment in R&D does not necessarily mean the pursuit of innovation, but also the accumulation of knowledge, essential in an uncertain environment. Freeman and Soete (1997) supports this argument when argue about the existence of two types of strategy for innovative firms: offensive and defensive. Firms with offensive strategies are in the technological leadership, operating on to the technological frontier and, therefore, employ different business strategies from firms furthest from the frontier. These firms require large volumes of R&D investments to maintain this position. In the other way, defensive strategy firms are followers, trying not to let their capabilities move too far from the technological frontier. To achieve this objective, R&D investment is also relevant, not so much for the development of new products and processes, but more to maintain the development of its internal capacities that allow it to identify and assimilate knowledge from the external environment.

Coad and Rao (2006) observed that innovation efforts, measured by investments in R&D, were more efficient when performed by market leading firms that were closer to the technological frontier of their industry. The market value created by "followers" investing in innovation was substantially lower compared to leading firms, suggesting that the follower firms should explore using existing technologies and imitating the technologies of firms closer to the technological frontier. From this perspective, the later firms must focus on improving production, while leading firms may seek new skills through diversification, growth, and export. Such statements have important implications for strategic decision-making as these decisions on investment in innovation are conditioned by the distance to the technological frontier occupied by the firm.

3. EMPIRICAL METHODOLOGY

3.1. Data Source and Sample Size

The database of the 2013 European Union (EU) industrial R&D investment scoreboard (European Commission, 2013) was used to measure the influence of innovative efforts in firm performance. These results, published in 2013, refer to 2012. The report is published annually and it provides a ranking of firms with the largest volume of spending on R&D. In addition, the information included volume of sales (€ millions), number of employees, capital expenditures (€ million), profitability, and growth measures, all specified for the base year 2012.

This ranking is updated every year, bringing information about changes in firms' investments in different periods of time. To maximize the sample size of 2000 firms (only available in the 2013 report), we opted for the unique database for that year. Since few changes have occurred over the years, a sample of 2000 firms is significant to the study's findings.

3.2. Definition of Variables and Econometric Modeling

To analyze the contribution of R&D to the financial performance of the firms, the variable operating income was used as proxy for performance. Thus, the model allows the analysis of the impact of R&D investment on the increased percentage of corporate profits as the efficiency score:

$$\textbf{EM.1} \quad log(\pi_{ijc}) = \beta_0 + \beta_1 \cdot log(R\&D_{ijc}) + \beta_2 \cdot \lambda_{\alpha}^{-1}(x,y) \cdot log(R\&D_{ijc}) + \beta_3 log(Capex_{ijc}) + \beta_4 \cdot log(L_{ijc}) + \gamma_j + \delta_c + \varepsilon_{ijc}$$

In equation EM.1, the variables π_{ijc}, $R\&D_{ijc}$, $Capex_{ijc}$, L_{ijc}, $\lambda_{\alpha}^{-1}(x,y)$ correspond to operating earnings, investment in R&D, investment in capital goods, number of employees, and the inverse efficiency score, respectively. The latter, by standard method, is a proportional adjustment to the output required to drive a firm (DMU - Decision Making Unit) towards the efficiency frontier. The concept of efficiency can be defined as the use of the fewest inputs (resources or x-vector) to produce the most outputs (production or y-vector). This idea is fundamental to most of modern benchmarking literature because it allows to evaluate performance without clearly defined preferences, especially in nonparametric methods like the partial frontier approach, in this case namely order-alpha. The score (output efficiency) calculated reflect the maximal proportional expansion of all outputs "y" that is feasible without using more resources (x-vector). The partial frontier approaches have several interesting properties that make them a very useful tool for empirical applications, because they are more robust to extreme values or outliers, especially more presents in the financial series.

By definition, the parameter takes on values $\lambda_\alpha(x,y) \geq 0 \therefore \forall\alpha \in]0,1]$, with the particular case of the total frontier $\alpha = 100\%$ where the partial frontier converges to a FDH frontier (free disposal hull). The values $\lambda_\alpha(x,y) \in (0,1)$ imply a slowdown in production as the firm approaches the efficiency frontier. In this case, these values represent the scores of super-efficient firms across the frontier. The score values $\lambda_\alpha(x,y) = 1$ represent the firms that operate on the efficiency frontier. Finally, $\lambda_\alpha(x,y) > 1$ represents the scores for the least efficient firms that need to increase sales proportion, given the vector of inputs, to ensure efficiency levels. Taking the inverse score $\lambda_\alpha^{-1}(x,y)$, it is assumed that values smaller than 1 are inefficient firms in proportion to the frontier values ($\lambda_\alpha^{-1}(x,y) = 1$). Thus, we use the values $\lambda_\alpha^{-1}(x,y) \in (0,1)$ as $\lim\{\lambda_\alpha^{-1}(x,y)\} \to 1$, so we may say that inefficient firms approach the efficiency frontier. Additionally, as the scores increase above the unit (1), the firms that move away from the frontier towards the DMUs tend to be super-efficient. Vectors represent the fixed effects for the characteristics of the sectors and countries that will be valued by dummy variables1. Finally, there is the error term that represents all the other factors that are out of statistical control and meets the criteria of normality $\varepsilon_{ijc} \sim N(0, \sigma_\varepsilon^2)$.

3.3. Estimation Method

The EM.1 equation can be estimated incorporating fixed effects that belong to the error term $\varepsilon'_{ijc} \equiv \gamma_j + \delta_c + \varepsilon_{ijc}$. However, regarding specific characteristics of certain sectors, especially when we differentiate between high, medium, and low technology, the pattern of investment is affected by inherent characteristics across sectors. Therefore, a strong association between the standard industry and the volume of investments is observed. In addition, some countries may implement specific laws that make investment in research more dynamic (Anderson, 1984).

Thus, the covariance between the coefficients and the stochastic disturbance is statistically different from zero, $cov(R\&D_{ijc}, \varepsilon'_{ijc}) \neq 0$. In this case, estimates by ordinary least squares (OLS) present biased and inconsistent results. To solve this problem, the fixed effects needed to be disaggregated from the stochastic disturbance. This method is commonly called ordinary least squares with dummy variables and consists of a multilevel method with parameters for the different sectors (γ_j) and different countries (δ_c). This alternative method is unbiased and consistent compared to OLS with traditionally grouped data (Cameron & Trivedi, 2005).

3.4. Calculating Efficiency Scores

Regarding the parameter of efficiency, $\tilde{\lambda}_\alpha(x,y)_{ijc}$,, being one of the variables from the regression model equation proposed in EM.1, it reflects the relative distance of each firm in terms of the frontier, given a combination of inputs required to achieve maximum production. Table 1 summarizes the combination of input-output in the estimation of efficiency scores:

[1] The 40 sectors were grouped into four main types: **High-tech**: Technology hardware and equipment, software and computer services, pharmaceuticals and biotechnology, healthcare equipment and services, and leisure goods; **Medium high-tech**: Industrial engineering, electronic and electrical equipment, general industrials, automobiles and parts, personal goods, other financials, chemicals, aerospace and defence, travel and leisure, support services, and household goods, and home construction; **Medium low-tech**: Food producers, fixed line telecommunications, beverages, general retailers, alternative energy, media, oil equipment, services and distribution, and tobacco; **Low-tech**: Gas, water and multi-utilities, oil and gas producers, nonlife insurance, industrial metals and mining, construction and materials, food and drug retailers, banks, electricity, industrial transportation, mobile telecommunication, forestry and paper, mining, and life insurance (Kancs & Siliverstovs, 2012). This procedure aimed to reduce the effects of a large number of parameters being estimated by dummy variables, which could result in serious damage to the model.

Table 1: *Variables definitions for calculating efficiency scores*

Variables	Variables Definitions	
Y	Total sales	
L	Number of employees	
K	Capex: investment in capital goods	
	Division of variables to calculate the scores	
	Output (y)	**Input (x)**
	Y	L
	-	K

Source: Own preparation

Based on the variables definitions in Table 1, the frontier per sector was calculated, totaling forty frontiers. For each sector, five quantile groups were created by efficiency score in partial frontier (25%, 50%, 75%, 95%, and 100%, the latter being the final frontier FDH - Free Disposal Hull) and for each conditional quantile a representative frontier was estimated. Thus, the total number of estimated frontiers was two hundred partial efficiency frontiers in the sample.

3.5. Retained Effects Interpretation

To measure the impact of investments on the dependent variable of the model, it was defined an elasticity coefficient as indicated in EM.2, which reflects the percentage effect that a particular variable has on another one. In the EM.1 model, this coefficient was calculated from the partial derivative of the logarithm of the operating profits in relation to the logarithm of R&D:

$$\textbf{EM.2:} \qquad \epsilon_{R\&D} \equiv \frac{\partial log(\pi_{ijc})}{\partial log(R\&D_{ijc})} = \beta_1 + \beta_2 \cdot \lambda_{\alpha}^{-1}(x,y)$$

Based on the coefficient in EM.2, the net effect of investments in research on operating profit partially depends on the calculated efficiency score, $\lambda_{\alpha}^{-1}(x,y)$. Depending on the estimated parameter sign (β_2), the approach to the frontier can leverage investments ($\beta_2 > 0$) or restrict them ($\beta_2 < 0$). A summary is presented in Table 2:

Table 2: Results matrix as expected from the sign parameter

Results matrix	**Sign Expected (β_2)**	
	Positive	**Negative**
Final effect $\epsilon_{R\&D}$	Growth effect moved by the frontier	Periphery effect driven by higher growth speed in firms to the most distance to frontier

Source: Own preparation

4. ANALYSIS OF RESULTS

Data analysis is divided into descriptive analysis, containing the data of firms in the sample for the year 2012 compared to previous years, and the quantitative analysis of the results of the proposed regression EM.1 model.

4.1. Descriptive Data Analysis

In 2012, firms that mostly invested in R&D increased those investments by 6.2% compared to 2011. Regarding sales, the situation was less rosy when comparing growth rates, with a year-over-year increase (2011-2012) of approximately 4.2% (a lower increase than the biennium 2010-2011 increase of 9.9% in sales).

In relation to specific groups, US and Japanese firms showed a significant growth, both in R&D and sales of approximately 8.8% and 5.8%, respectively. Although this growth was quite significant, given the recent effects of the global economic crisis, East Asia has shown strong leadership in growth, especially in R&D, for firms from China (12.2%), South Korea (8.9%), and Taiwan (8.2%). A summary addressing the growth rate of the variables, considering the total sample of firms, can be seen in Table 3.

Table 3: Variables growth rate.

Variables	Growth Rates (%)	
	2011-2012	2009-2012*
Inv. R&D	6.20	6.40
Sales	4.20	8.50
Capex	9.60	9.30
Profit	-10.10	10.00
No. Employees	1.50	3.40

Source: Own preparation
Note: (*) CAGR - Compound annual growth rate.

In the three-year period 2009-2012, the average growth rate in R&D investment among the sample firms was approximately 6.4%. Although the growth rate in sales showed a value below the growth rate in investments in the year-over-year results, over the three-year period this pattern was not observed, showing instead a growth rate in sales of 8.5%, which was higher than the 6.4% growth in investments.

In terms of the investment in capital goods (Capex), the growth rate of firms year-over-year was slightly higher than the three-year period 2009-2012, 9.6% versus 9.3%, respectively. Only in terms of profits this difference was discernibly more noticeable.

Another important aspect of the sample corresponds to sector groups: high, medium-high, medium-low, and low-tech. The high-tech sectors led, in terms of volume of investments in R&D, with 317.6 million euros, versus 263.7 million in medium-high sectors, 183.5 million in medium-low sectors and 166.5 million in the low-tech sectors. Descriptive statistics of the model variables are presented in Table 4.

Table 4: Sample descriptive statistics

Variables	Average	Percentile				Max.
		25%	50%	75%	95%	
Inv. R&D (€ million)	269.38	35.80	63.50	156.35	1,103.50	9,515.00
Sales (€ million)	8,495.17	583.15	1,883.70	6,150.70	38,370.90	354,000.00
Capex (€ million)	617.88	21.30	80.40	311.50	2,480.70	37,566.30
Profit (€ million)	776.71	23.50	126.10	462.00	3,695.70	48,539.50
No. Employees	26,515.60	2,436.50	7,970.50	22,545.00	118,087.00	548,355.00

Source: Own preparation.

According to Table 4, the average investment in R&D in 2012 was 269.38 million Euros. Comparing the average with the percentile values, we can observe an asymmetry in the data. Regarding the median, 50% of firms had a maximum investment of 63.5 million euros. Therefore, the average is leveraged especially in higher percentiles, well above the 75% percentile (75% of firms had a maximum investment of 156.35 million euros). In all the other variables, the mean value is situated in percentiles higher than 75%.

Sales on average for the year were 8,495.17 million euros, quite above average, with 50% of the firms with sales at most 1,883.7 million euros. As for the profits, they had a mean value of 776.71 million euros. This value was also quite above average, where 50% of firms had a maximum profit of 126.1 million euros. Finally, investments in capital goods showed an average amount of 617.88 million euros. Again, this value outperformed the median, with 50% of firms having invested no more than 80.40 million euros.

4.2. Quantitative Analysis: Model Estimates

The first results of the EM.1 equation model is presented in Table 5, excluding fixed country effects.

Table 5: EM.1 Model Results

VARIABLE	Partial Frontier				FDH
	25%	**50%**	**75%**	**95%**	
log(R&D)	0.287***	0.308***	0.273***	0.270***	0.0426
	(0.0326)	(0.0343)	(0.0323)	(0.0340)	(0.0423)
log(Capex)	0.423***	0.423***	0.420***	0.423***	0.466***
	(0.0305)	(0.0287)	(0.0290)	(0.0279)	(0.0283)
log(L)	0.272***	0.271***	0.265***	0.267***	0.290***
	(0.0313)	(0.0314)	(0.0318)	(0.0320)	(0.0298)
log(R&D)* $\lambda^{-1}_{\alpha=25\%}$	0.000238***				
	(0.00005)				
log(R&D)* $\lambda^{-1}_{\alpha=50\%}$		0.000540			
		(0.000364)			
log(R&D)* $\lambda^{-1}_{\alpha=75\%}$			0.00383***		
			(0.000761)		
log(R&D)* $\lambda^{-1}_{\alpha=95\%}$				0.0161***	
				(0.00401)	
log(R&D)* $\lambda^{-1}_{\alpha=100\%}$					0.239***
					(0.0240)
Constant	-0.0629	-0.135	0.0840	0.0564	0.442*
	(0.301)	(0.327)	(0.334)	(0.333)	(0.266)
Fixed Effects					
--Countries	No	No	No	No	No
--Sector Group	Yes	Yes	Yes	Yes	Yes
Sample	2000	2000	2000	2000	2000
R^2	0.701	0.699	0.701	0.701	0.720
R^2 – Adjusted	0.699	0.697	0.699	0.699	0.719
Wald Chi test^2	3038***	3230***	3756***	2995***	2939***
Heteroced test. Chi^2	8.58***	7.45***	7.76***	7.33***	5.86**
Ramsey F RESET test	0.32	0.11	0.62	0.45	0.81

Source: Own preparation
Note: The dependent variable is the logarithm of operating profits. The asterisks *, **, *** correspond to significance levels of 10%, 5%, and 1%. The standard error estimates are heteroscedastic robust, via the *Bootstrap* technique using 400 sample replicates.

According to the results shown in Table 5, the first column indicates the estimates by taking the 25% quantile as the definition of the partial frontier. Thus, efficient firms have a 75% probability of being "dominated" by other firms in achieving the same level of production from less intensive inputs (inputs saving). In this partial frontier for low-performing firms in the input-output relation, an increase of 1% in investment contributes to an average growth of 0.29% in profits (significant at 1%). Compared to the elasticity of investment in capital goods, the average impact among firms was 0.42% (significant at 1%). Regarding the elasticity of labor, an increase of 1% in the number of employees contributed to an average growth of 0.27% in profits, standing just below the elasticity for R&D for the frontier firms (significant at 1%).

The model explanatory power was moderate and presented a great adjustment quality (very close to the R2). Thus, 70% of the variations in earnings were explained by the model variables. The Chi test2 reveals that the estimated parameters together are relevant and statistically different from zero (null hypothesis rejected at 1%). The heteroscedasticity test rejects the null hypothesis of constant variance, revealing the necessity to correct the estimates of standard error of the model (bootstrap). Finally, the reset test does not reject the null hypothesis that the model is not affected by problems associated with omitted variables. In this case, it can be concluded that the model is correctly specified (not reject the null hypothesis at the 10% level).

Analyzing the three upper quantiles (50%, 75%, 95%), partial elasticity gradually increased investment associated with an increased quantile. While the probability of dominance lessens and the partial moving frontiers move toward the end frontier (100% Quantile or FDH scoring method), the effect of the relative investment on profit contribution increases. Comparing the scores of the frontier between the different quantiles, the partial elasticity of R&D increases to 0.00054 (50%), 0.00383 (75%), and 0.0161 (95%) - all significant at 1%. Comparing these parameters with the first quantile estimate, the evolution corresponded to 2.3 times (50%), 16.1 times (75%), and 67.6 times (95%), respectively. This growing evolution highlighted a notoriously higher contribution in firms with less likelihood of dominance (efficient firms with higher performance observed in the upper quantiles). The other elasticities suffered minor variations due to changes in the interaction between efficiency scores and investments in R&D.

Regarding the statistics of the model explanatory power and adjustment quality, all featured quantiles presented subtle changes in relation to the first quantile (small variations of moderate to significant amounts). The same can be observed in the heteroscedasticity tests, rejecting the null hypothesis at all quantiles constant variance in the model (at the 1% level). Once again, the reset test did not reject the model null hypothesis correctly specified in the other quantile (not reject the null hypothesis at the 10% level).

Finally, there is a final frontier or FDH score method. Unlike the traditional data envelopment analysis (DEA) approach, the FDH method relaxes the convexity hypothesis in the production measurement due to the fragility of evidence associated with the indivisibility of inputs, economies of scale and scope, and market imperfections (Simar & Wilson, 2013). In this case, there is a clear bias in the parameter linked to the frontier score, a difference of 14.8 times compared to the 95% quantile. In addition, the parameter of the variable "log (R&D)" showed a divergence in relation to other estimates, and beyond that no statistical significance.

Although the quality of the adjustment has shown a relative increase, this improvement occurred with a drop in the significance of the global validity of the statistical model and the heteroscedasticity test (even if such statistics had not shown divergence from past results). Again, the reset test did not reject the null hypothesis of the correctly specified model. The results in Table 6 show the estimates of the EM.1 model now including the fixed effects for countries.

According to Table 6, the average elasticity of R&D (log(R&D)) declined gradually between quantile 25% and 95% (all significant at 1%). Regarding investments in capital goods, the results were very similar with slight variations between the quantiles (significant parameters 1%). The same can be seen with the number of employees, whose elasticity between quantiles remained very close and significant at the 1% level (all quantiles).

In relation to the partial elasticity linked to efficiency scores, we could observe a positive and significant parameter in all quantiles analyzed. In the first quantile (25%), the frontier firms show an average increase in the elasticity of R&D of approximately 0.00023% compared to other firms. Comparing other quantiles with the first, the parameter has a growing evolution of 2.7 times (50% quantile), 18.5 times (75% quantile), and 77.1 times (95% quantile) higher compared to the 25% quantile. This increasing effect as a result of lower dominance for frontier firms reveals, as in previous results, a gradually greater impact on the most efficient firms of higher levels in the input-output ratio (higher performance observed in the upper quantiles).

Assuming the full frontier (100% quantile or FDH score), the partial elasticity linked to the frontier presents a result a thousand times superior to the first quantile and thirteen times compared to the 95% quantile. It reveals the score sensitivity when setting the outlier firms (FDH frontier) against the other firms in the sample. This sensitivity is also seen in the non-significance of the mean parameter of R&D (log(R&D)).

Table 6: EM.1 Model Results

VARIABLE	Partial Frontier				FDH
	25%	50%	75%	95%	
log(R&D)	0.259***	0.274***	0.235***	0.234***	0.0289
	(0.0324)	(0.0335)	(0.0333)	(0.0338)	(0.0397)
log(Capex)	0.438***	0.438***	0.435***	0.439***	0.481***
	(0.0285)	(0.0286)	(0.0282)	(0.0284)	(0.0277)
log(L)	0.279***	0.278***	0.272***	0.273***	0.289***
	(0.0322)	(0.0323)	(0.0320)	(0.0324)	(0.0317)
log(R&D)* $\lambda^{-1}_{\alpha=25\%}$	0.000227***				
	(0.000041)				
log(R&D)* $\lambda^{-1}_{\alpha=50\%}$		0.000602**			
		(0.000288)			
log(R&D)* $\lambda^{-1}_{\alpha=75\%}$			0.00420***		
			(0.000706)		
log(R&D)* $\lambda^{-1}_{\alpha=95\%}$				0.0175***	
				(0.00362)	
log(R&D)* $\lambda^{-1}_{\alpha=100\%}$					0.231***
					(0.0220)
Constant	-0.0270	-0.0799	0.145	0.112	0.514*
	(0.330)	(0.336)	(0.336)	(0.330)	(0.290)
Fixed Effects					
--Countries	Yes	Yes	Yes	Yes	Yes
--Sector Group	Yes	Yes	Yes	Yes	Yes
Sample	2000	2000	2000	2000	2000
R^2	0.739	0.738	0.740	0.740	0.757
R^2-Adjusted	0.730	0.728	0.731	0.731	0.748
Wald Chi test^2	8149.48***	2691.19 ***	5261.76 ***	2797.75 ***	4626.74***
Heteroced test. Chi^2	25.75***	24.85***	25.54***	25.14***	20.41***
Ramsey F RESET test	0.43	0.28	0.57	0.51	0.55

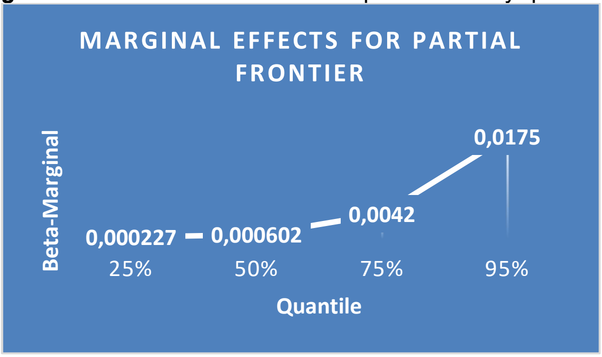
Source: Own preparation

Note: The dependent variable is the logarithm of operating profits. The asterisks *, **, *** correspond to significance levels of 10%, 5%, and 1%. The standard error estimates are heteroscedastic robust, via the Bootstrap technique using 400 sample replicates.

The model fit (R2) was high when compared to the method that excluded the fixed effects of countries. Likewise, the adjustment quality was also satisfactory with an adjusted R2 very close to R2. This quality was also reflected by the reset test, which did not reject the null hypothesis of the model being correctly specified (there was no evidence of problems associated with omitted variables). In all quantiles, the heteroscedasticity tests showed rejection of the null hypothesis homoscedastic errors.

Figure 1 illustrates the trend towards greater positive impact on the frontiers with less likelihood of dominance (frontiers located at the upper quantiles). The final frontier (quantile 100%) was excluded in order to avoid a disparate trend in the graph due to the bias caused by the outliers of the sample.

Figure 1 **-** Evolution of the selected parameters by quantile.



Source: Own preparation

5. DISCUSSION WITH RECENT RESEARCH

The concept that firms' competitive strategies are conditioned by their position on the frontier consists of a guided approach based on the contributions of Schumpeterian innovation literature. According to Dosi (1982), the most significant technological and economic dimensions that define the highest level of technology achieved are commonly attributed to the concept of the "technological frontier." Thus, firms that meet this criterion have a set of very different strategies than firms operating "behind these frontiers."

In this way, recent studies have shown this vector of influence in different investment contexts, specifically the contributions of Coad (2008; 2011), Reinstaller and Unterlass (2012), Hall, Lotti, and Mairesse (2013), and Hölzl and Janger (2014). Coad (2011) presented empirical evidence that firms located on the frontier employ R&D resources more efficiently, generating significantly higher scores than the more distant firms. To measure the concept of frontier, we used the quantile regression method. By defining that in the firms located at the upper quantiles, the average of the dependent variable was greater than for the lower quantiles. Thus, the results of this research showed that the lower quantile parameter associated with investments had a negative impact on the dependent variable (Q-Tobin). This effect showed a shift to positive, especially in the upper quantiles where the average Q-Tobin value was higher.

According to Hölzl and Janger (2014), the perception of barriers to innovation is statistically higher for firms present in more distant regions from the technological frontier. In this sense, in the same manner that the percentage of innovative firms decreases with greater distance to the frontier, the relative number of firms that do not give much importance to innovation increases as well.

> This is consistent with the idea that as firms approach the technological frontier, they increasingly need to focus on the creation of their own knowledge and the adoption of innovation-based growth strategies to stay competitive. (Hölzl & Janger, 2014, p. 707)

Although the findings are consistent with recent research, other innovation-related activities, but not directly related to R&D investments, can be influenced by firm's technological position. Particulary, Lopez-Rodriguez and Martinez-Lopez (2017) deal with quite properly on this subject. Many innovation activities, such as small firms, selectively more restricted of internal innovative capacity, on skilled labor provision, among other factors, are more likely to innovate without making direct investments in R&D. This lack of treatment of the model can significantly influence the relation between R&D and the measure of performance, which may reflect a "cost" of overestimating the impact of the investment. Although a more thorough treatment of the empirical method seeks to distinguish the heterogeneous effects of R&D investments by 'smoothing' their uniform impact on the sample, future researches approaching the present model to the authors' study may help to better understand the relation between 'R&D versus performance' of firms.

6. ROBUSTNESS OF RESEARCH

The analysis of the influence of investments in R&D on the performance of firms has always dealt with important questions that condition the demand for such investments. This implies an endogeneity pattern of the investment series that makes relevant the control of the model. In this sense, it is important to highlight the reasons that are responsible for motivating firms to invest in their innovation activities.

In a recent research, Barge-Gil and López (2014) investigated the determinants of R&D investment from a sample of Spanish firms over a short panel (2005-2009). The results showed that firm size and market share are important predictors of the behavior of investment decisions, since they reflect characteristics that distinguish firms in different technological positions.

Similar results were also presented in Inderrieden, Laczniak and Pecotich (1990) (with lagged investments in R&D), Cumming and Macintosh (2000) (early-stage firms apply more research investments in relation to the more consolidated firms and with a higher debt-to-equity ratio), Lee (2003) (firm size aligned with technological competencies within the sector), Mishra (2007) (market share and human capital engaged in research activities) , Chun and Mun (2012) (knowledge spillovers), Máñez et al. (2015) (unrecoverable research costs and the demand-pull hypothesis) and Doloreux, Shearmur and Rodriguez (2016) (firms' internal capabilities, strategic alignment to the external market, and the sectorial innovation pattern).

The literature presented highlights the potential "costs" of endogeneity relating the company behavior and the R&D investments. In the presented results, however, we investigate the impacts of these investments on the performance of firms and how this impact is associated with the firm's position in relation to the technological frontier.

In this case, part of the endogeneity is captured by the firm's technological position, in addition to incorporating an alternative way to evaluate this position according to different types of frontier and "dominance" within the sample. This alternative form incorporates important information, capturing heterogeneity factors in the sample, according to recent contributions by Coad and Rao (2006) and Coad (2011).

In spite of results observed are in agreement with recent research, there are activities related to innovation that may not be directly linked to investments in R&D. This may lead to an overestimation of the relationship between variables, according to recent contributions by Lopez-Rodriguez and Martinez-Lopez (2017). Although the present study adopts a more robust technique to measure the technological frontier, or even different partial frontiers converging to a final frontier, future research, applying this technique for innovative activities, but not linked to R&D investments, can offer an important support to be testable to the model. This procedure aims to expand the study on different research fronts within the theme, increasing the understanding about the relation between these variables.

It should be observed that, while the present model disregards the potential effects of endogeneity on the model, statistical costs can be minimized as we incorporate alternative ways of analyzing the relations between variables. In addition, we emphasize that endogeneity consists of a feasible problem and that the presented results are coherent with associations and not to cause-effect relations between the variables of the model.

7. FINAL CONSIDERATIONS

This study investigates the impact of R&D investments on firm profits according to different levels of efficiency. To capture a firm's efficiency vector, we used the latest non-parametric method of frontier analysis: order-α partial frontier. This method builds different frontiers, called partial boundaries, as each quantile is specified. Unlike the standard DEA approach with free availability (FDH), the outliers have considerable influence on the definition of scores because they are treated as the actual frontier data. Thus, different frontiers begin to consider the extreme values as super-efficient units, disregarding the influence of these units in the scores of the least efficient firms.

The analysis of efficiency scores and firms' investments in R&D allowed the estimation of the investment elasticities on firm profits. The results show that the most efficient firms have higher investment elasticity coefficients in relation to higher operating profits than the least efficient firms (those furthest from the frontier). This pattern was observed across different quantiles. Thus, in the lower quantile, the influence of investment scores proved to be less than in the upper quantiles.

Therefore, this shows that the most efficient companies on the efficient frontier make more profits with the same level of R&D investment, compared with less efficient firms. Thus, firms on neighborhood of the frontier area aggregate greater value through the relation between profits and investment in R&D.

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