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The Impact of R&D Investments on Performance of Firms in Different Degrees of Proximity to the Technological Frontier

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Abstract

This study analyzes the impact of R&D in the performance of companies from different degrees of proximity to the technological frontier. In this way, a model of endogenous growth was built, where firms operating closer to this frontier use the research resources to move it, enjoying a higher return. To test this hypothesis, we used a sample of companies with major investments in R&D in the world, according the ‘EU Industrial R&D Investment Scoreboard'. Then, an indicator that measures the degree of proximity to the frontier for each sector was built. Through the technique of regression with panel data, it was estimated an equation where the performance metrics of the company is conditioned by investments in R&D and the investment interacted with the proximity index to the frontiers. Thus, the impact of investments in performance is represented by two important vectors of influence: (1) the average effect of investments on performance, represented as a direction of the sector in demand for investment; (2) the effect-efficiency that determines the company's strategy as its position in relation to the established frontier. The results show that, as the firms get closer the technological frontier, the greater is the return of investment in R&D on performance. These results indicate that the advancement of economies towards the frontier or the best technological practices depends on policies that incorporate the influence of the 'development stage' in the outcome of this policy.

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1. Introduction

Innovation is increasingly essential in a highly dynamic market, where changes occur at ever increasing speed. In this environment, innovation is no longer an option: it is essential for firm's survival. As Freeman and Soete (2008) argue, firms that do not innovate move to death. The innovative activity, with its high failure rate, is one of the highest risk activities of the modern corporation, as argue Cooper (2003) and Pavitt (2005). Here, we refer to innovation as search, discovery, experimentation, development, imitation and adaptation of new products, new processes and new organizational formats (Dosi, 1982; 1988).

Therefore, investment in research and development is essential to promote innovative gains. This investment is not a superfluous item of firm strategy but, according to Bessant (2003), imperative for their survival. For Itami and Numagami (1992), there is a direct correlation between the strategy to be adopted and the development of new technologies.

Many researchers have focused on this field to build a link between the efforts in creating new products, processes and organizational forms and the consequences of these efforts on the financial performance of firms (Lazonick, 1992; Teece, 2009). In this sense, targeted policies aimed at accumulation of dynamic capabilities of firms have been treated as fundamental to the development of any economy, especially in the newly industrializing economies (Amsden, 2001). Other researches have attempted to measure the effect of innovative efforts in the performance of firms, incorporating in the analysis the concept of proximity to frontier (Acemoglu, Aghion and Zilibotti, 2006; Aghion, Howitt and Aghion, 2009; Hall and Lerner, 2009; Coad, 2011).

In accordance with these discussions, recent studies (Coad and Rao, 2006; Coad, 2008; 2011; Kancs and Silverstovs, 2016; Montresor and Vezzani, 2015) have shown that investments in R&D have different results according to the different degrees of proximity to the technological frontier. By quantile regression, Coad (2008; 2011) analyzed a sample of firms in different sectors and noted that firms located nearest the frontier (upper quantiles of the conditional distribution) had higher return on investment in R&D. The study results suggest that firms closer to the technological frontier employ investments in research designed to move the frontier, appropriating the economic results arising from this displacement process.

Although these results are consistent with the literature of endogenous growth models, as the contributions of Aghion and Howitt (1998, 2009), the studies presented by Coad (2008; 2011) fail to capture important aspects related to the true nature of the factor 'proximity to the frontier'. The restriction of this study derives from an important emphasis on technique. As Daraio and Simar (2007), the linear regression techniques do not capture, in a precise way, important characteristics of a technologically efficient production, even considering different points of the conditional distribution. The production structure at the fronteir can be distinguished from an average production structure constructed by a data sample. The 'best practice' does not necessarily imply an "average practice', since it does not incorporate aspects of the economies of scale and scope.

Our research contributes on this issue, analyzing the effects of the approach to the frontier through a more consistent technique. In this sense, it was estimated efficiency scores from non-parametric technique of Free Disposal Hull (see Appendix B). Taking a sample of 548 firms that have invested most in R&D between 2003 and 2013, we could observe that the most efficient firms have higher elasticity coefficients in R&D in relation to the most inefficient firms, indicating that the more distant from efficient frontier employ investments in research with lower efficiency or tend to have higher opportunity costs in the use of these investments. Even though converging with the conclusions highlighted by Coad (2008; 2011) and Montresor and Vezzani (2015), these results have greater consistency with the literature presented.

2. Theoretical framework

2.1. R&D Resources as Strategic Investment

Investments in R&D became increasing in firms throughout the twentieth century. It denotes a deep change of the production process, representing an essential aspect of the great social and economic transformation in this period. Since the contributions of Arrow (1962), spending on R&D began to be perceived with quite peculiar characteristics compared to other investment of the firm. At a first glance, such investments are conformed to uncertainty. So, they compete with other investments (physical capital) according to the best and "safest" return. In another perspective, resource constraints by firms make investments in R&D highly selective, since the most advanced companies employ such resources more efficiently to move the 'technological frontier' of the sector they operate. Regarding firms with low technological learning, the displacements of the frontiers have the effect of increasing its relative distance, enhancing the opportunity costs of these investments and reducing the effectiveness of the results, as that imitative strategies increase the competition for resources (Coad, 2011).

Hall (2002) argue that there are large differences between investments in R&D and in physical capital. At First, the investment composition is very different: more than half of the resources are expended on paying salaries for a workforce highly skilled and trained. Because of this organic composition (since it reflects the dynamism of technology), most of the knowledge created becomes intangible and tacitly incorporated in engineers and researchers. This fact has two related consequences: the propriety of this knowledge does not lie entirely in the firm. This encourages the development of specific contracts for these investments, aiming to keep employees with valuable company assets: the knowledge (Hall and Lerner, 2009).

This pattern of behavior is better observed in the firms located nearest to the frontier, where competition for knowledge is more intensive. Empirical evidences show that competition among the most advanced firms has the effect of forcing them to innovate as a strategy to escape of the effect of "threat to entry", whose incoming firms promote to those which are established. This strategy has a positive relation with the probability of entry, linking innovation and ‘threat to entry’ to a distinct pattern in relation to less developed firms. In this specific case, firms are discouraged to innovate, since firms, collectively, destroy the value of their innovations, increasing the opportunity costs of investments in R&D (Aghion and Bessenova, 2006).

Therefore, the results of investments in R&D are closely linked to fluctuations in relation to proximity to the frontiers (Acemoglu, Aghion and Zilibotti, 2006). For this reason, it is essential to analyze factors that reflect the innovative efforts of firms considering their effects on the establishment of technological asymmetries, especially when such asymmetries influence most of the dynamic capabilities of firms (Teece, 2009). A dissociated analysis between these factors could result in inaccurate conclusions about the true nature of the 'paradigm of technology'.

2.2. Innovation and Economic Environment

The approach presented below consists in a variation of the methodology proposed by Aghion and Howitt (2009). It occurs on an environment where firms operate in a competition with others in a specific industrial sector. Each firm has a production function that approximates to a traditional Cobb-Douglas function: $Y_{it} = (k_{it})^{\alpha}(L_{it}A_{it})^{1-\alpha}, \alpha \in (0,1)$ (1)

According to equation (1), the elasticity of the stock of physical capital (k_i) of the i-th firm is represented by the parameter α. Consequently, the elasticity of the number of employees of the firm (L_i) and of technological parameter (or total factor productivity) from the firm (A_i) is represented by $(1-\alpha)$, so that the firm presents constant returns of scale. The time is limited in a horizon of T-years, t = 1,2,3,4 ... T.

If the firm implements an innovation to market, the improvement of the product is accepted and the technological parameter consists in an advance of improvement over the previous period. If the firm does not develop an innovation, technological status will be the same of the previous period, without notice any improvement. $A_{it} = \begin{cases} \gamma A_{it-1};\ \mu \\ A_{it-1};\ 1-\mu \end{cases}$ (2)

According to equation (2), the parameter $\gamma > 1$ corresponds to the extent of innovation and increase of the technological parameter of the firm in relation to the lagged period with probability μ of a succeed innovation. Otherwise, $1-\mu$, the firm fail in the innovation and the quality of your product do not improve over the previous period. The rate of technological progress of the firm is represented by the mathematical expectation *E(.)* in the percentage change of the technological parameter: $g_A = E\left(\frac{A_{it}-A_{it-1}}{A_{it-1}}\right) = \mu(\gamma-1)$ (3)

The probability of success of firm's innovation depends on the volume of funds invested in innovative activities, which associates each investment in research (n) to a probability of success (μ) research, according to the following notation: $\mu = \theta(n_{it})^{\sigma};\ \sigma \in (0,1)$ (4)

In accordance to the innovation function above, the parameter θ reflects the research productivity and is admitted being a strictly low value to ensure the probability interval μ. The $\sigma \in (0,1)$ parameter represent the elasticity of research in increasing the probability of successful of innovation (Aghion and Howitt, 2009; Acemoglu, Aghion and Zilibotti, 2006).

The growth rate in sales of the firm consists in the following algebraic solution:

$$g_Y = \alpha g_k + (1-\alpha)(g_A + g_L) \quad (5)$$

Without a considerable loss of generality, the growth rate of capital (g_k) and workers (g_L) will be considered equal to zero. Substituting equations (3) and (4) into (5):

$$g_Y = (1-\alpha)\theta(n_{it})^{\sigma}(\gamma-1) \quad (6)$$

From equation (6), we present the first test proposition in this study:

- **Proposition 1:** *Investments in R&D contribute to the growth of sales by increasing the likelihood of success on future innovations in the firm.*

As proof of **Proposition** 1, we can apply the concept of partial derivative in the growth rate with respect to investments in R&D: $\frac{\partial g_Y}{\partial n_{it}} = \frac{\sigma(1-\alpha)(\gamma-1)}{\theta(n_{it})^{1-\sigma}} > 0$ (7)

According to equation (7), the investments in R&D contribute visibly to the growth of firms. However, we may ask which firms enjoy a greater contribution to growth and which have marginally lower increments? What factors affect the elasticity of research in different contexts of firms?

To answer such 'theoretical puzzles', we will use the methodological assumption proposed by Aghion and Howitt (2009). According to the authors, for firms that are more distant from the sector leadership, the strategies based in the implementation of technologies from the frontier tend to result in a rapid contribution on growth of these firms, what do not happen with firms located in 'the vicinity of the frontier'. Thus, the different results associated with the research activities present patterns of sensibility in relation to fluctuations in the proximity to the frontier.

In this perspective, the frontier is defined as the reference technology in the industry sector. Therefore, each firm has limits based on the firm that own the "leadership status". On this assumption, the firm located on frontier ($\bar{A}$) is that firm which owns the reference of technology, satisfying as the limit of knowledge within the sector $A_{it} \leq \bar{A}$. Thus, both productivity and the elasticity of the research are affected by the degree of proximity to the frontier $a_{it} = A_{it}/\bar{A}$ (it is said that $\theta(a_{it})$ and $\sigma(a_{it})$ are increasing functions of the technological approach, $\theta'(a_{it}) > 0$ e $\sigma'(a_{it}) > 0$). Thus, the greater the proximity to frontier $\lim a_{it} \to 1$, the greater the contribution from productivity and from the research elasticity on the success of the innovation, because the experiences and patterns of cumulative knowledge in consolidating the technological trajectory (Teece, 2009).

This positive correlation between R&D investments and firm growth is empirically validated in Coad and Rao (2008, 2010a, 2010b, 2011) studies. Although Coad and Rao (2008, 2010a) have shown a positive correlation between investments and firms 'growth (in relation to other studies from these authors), their findings deepen the theme by indicating a heterogeneous form of this relationship. Through the quantile regression technique, the authors indicate that this relation is more prominent in firms of highest growth, signaling that firms located in the upper tail of the distribution of growth obtain a higher return from the applied investments.

- **Proposition 2:** *The contribution of investments in R&D to the growth of sales is higher for firms located near the frontier than for the more distant firms.*

$$\frac{\partial g_Y}{\partial n_{it}} = \sigma(a_{it})(1-\alpha)\theta(a_{it})(n_{it})^{\sigma(a_{it})-1}(\gamma-1) > 0 \quad (8)$$

Applying the partial derivative with respect to the degree of proximity to frontier, we have the marginal effect of technological approach in the contribution of investment in research on growth: $\frac{\partial^2 g_Y}{\partial n_{it}\partial a_{it}} = \frac{\sigma(a_{it})(1-\alpha)\theta(a_{it})(\gamma-1)}{(n_{it})^{1-\sigma(a_{it})}}[\Omega(a_{it})] > 0 \blacksquare$

$$\Omega(a_{it}) \equiv \left[\left(\frac{1+\sigma(a_{it})ln(n_{it})}{\sigma(a_{it})}\right)\sigma'(a_{it}) + \frac{\theta'(a_{it})}{\theta(a_{it})}\right]$$

3. Empirical Methodology

3.1. Definition of the sample

The report "The EU Industrial R&D Investment Scoreboard" includes economic and financial data of companies with larger investments in R&D from all the world, comprising the largest investors selected and classified by the level of these investments. These data are available according to the latest available balance of these firms. The annual reports and accounts are public domain documents and organized by the department Industrial Research Monitoring and Analysis (IRMA) from the European Commission. The collected data are adjusted by the corresponding exchange rates in the annual reports using as reference the rate from December 31 of each year. In addition, the monetary values for each variable are expressed in millions of euros. Except for the growth variables in the report, the proportions between the variables are expressed in percentage units. The variable that measures the stock of workers in each firm is presented through the number of employees and cataloged at the end of the fiscal period.

This sample represents an important representation of innovation efforts in the world, since the data include major firms investing in R&D, accounting for a share of 90% of all investments in research in the world (European commission, 2014). The total of firms in the study consisted in a set of 548 firms between 2003 and 2013. The final panel consisted of a sample of 6.028 observations. In this way, it should be noted that recent researches on innovation has been adopting this database, considering that it includes the largest innovation investors in the world, especially Castellani et al (2017), García-Manjón and Romero-Merino (2012) and Montresor and Vezzani (2015).

3.2. Econometric model

The estimated model consisted of the following equation:

me.1 $$log(y_{it}) = \alpha + \beta_1 log(R\&D_{it}) + \beta_2 log(R\&D_{it}) * \theta_{it}(x,y) + \beta_3 log(K_{it}) + \beta_1 log(L_{it}) + \delta_i + \tau_t + \varepsilon_{it}$$

As me.1 equation, the variables $(y_{it}, R\&D_{it}, \theta_{it}, K_{it}, L_{it})$ correspond, respectively, to sales, R&D efficiency score, investment in capital goods and the stock of labor of the company "i" in time "t" (see Appendix A). Regarding the efficiency score, the next topic will present methodology to get it, based on the technique of Free Disposal Hull.

The variables (δ_i, τ_t) represent the fixed effects for the specific attributes of firms and temporary shocks of random nature, but which are common between firms. Finally, the term stochastic perturbation $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, which captures all the other factors that are irrelevant to the model structure. Hypothesis tests on the behavior of stochastic perturbation will be applied in order to ensure the efficiency properties of the model.

3.3. Scoring Efficiency

The measurement of the efficiency degree from several companies do not always consists in a simple exercise. Traditional techniques of linear regression do not capture accurately some important characteristics of a technologically efficient production. The production structure at the frontier can be different from an average production structure constructed by a data sample. The 'best practice' does not necessarily imply an "average practice", since it does not incorporate aspects relating to economies of scale and scope (Daraio and Simar, 2007).

To capture the effect of the efficiency of firms, efficiency scores was obtained using a non-parametric technique, called *Free Disposal Hull*. The advantages of this technique are summarized in Appendix B.

In this way, this study will apply FDH technique to estimate firms' efficiency scores. Considering the selected sample, it was identified 40 sectors in which firms are distributed. For each sector, in each time point was constructed a frontier of efficiency-oriented input. So, it was obtained 40 frontiers.

The variables selected for calculation of efficiency scores are presented in the following table:

Table I: Definition of variables to calculate the efficiency scores.

variables	Definition of variables	
Y	Profitability	
L	Total of employees	
K	Intensity of investments in capital goods	
	Division of variables to calculate the scores	
	output	**input**
	Y	L K

Source: developed by the authors.

The input-oriented method for calculation of efficiency scores assumes that companies minimize inputs for a given level of production (in this case, profitability). Thus, the calculated scores is a proportional adjustment in input to drive firms inefficient to an efficient level of use of inputs. Therefore, the scores take values in the following range: $\theta_{it}(x, y) \in [0,1]$

As the distribution of results of the scores, the closer to zero the calculated score is, $\lim\theta_{it}(x, y) \to 0$ or $\lim\theta_{it}(x, y) \to 1$, the more inefficient the company is located, and when the score approaches the opposite limit, the more efficient the company is and, therefore, nearest the frontiers is its location.

3.4.Estimation method

Depending on the data nature, the parameters will be estimated through three important techniques: (1) fixed effects; (2) random effects, and (3) OLS with pooled data (OLS Pooled).

The first technique incorporates the effects of heterogeneity of the sample (δ_i, τ_t) on the specific attributes of firms and temporal random nature shocks (Cameron and Trivedi, 2005). Such factors can be correlated with the regressors, since forms of organization may induce the demand for investments and gains associated with the own efficiency. In this case, the absence of inclusion in the main model can lead to a serious error of specification, contributing to the emergence of endogeneity problems.

Otherwise, gains on the efficiency can be obtained by including such factors as uncorrelated with the regressors. These gains come from an alternative technique known as a method of random effects (Hayashi, 2000; Wooldridge, 2010). This approach yields parameter estimates from the generalized least squares method (GLS).

To identify which technique is the most appropriate, it will be employed the Sargan-Hansen test with the null hypothesis that the fixed effects are not statistically correlated with the covariates of the model. The use of this test over the traditional Hausman (1978) is that in the former case, the test has to be more robust as the presence of problems related to heterocedasticity and autocorrelation (Wooldridge, 2010).

Finally, a comparison with the traditional technique of OLS excludes heterogeneity factors in the sample without the technical work properly to ensure the efficiency gains compared to the technique of random effects.

3.5.Robustness of estimates

To detect violations relating to heterocedasticity and autocorrelation, it was applied two important tests. In the first case, the statistic modified of Wald for models with fixed effects, which null hypothesis implies that $H_0\colon \sigma_i^2 = \sigma^2, \forall i \in \{1,2, \ldots N\}$. In this case, the non-rejection of null hypothesis implies that the regression residuals are distributed in a homoscedastic form (Greene, 2000, p. 598). To the pooled OLS method, it was applied the test of Breusch and Pagan (1979) under the same null hypothesis.

The second test involves checking the existence of autocorrelation in accordance with the test of Wooldridge (2002). The Wooldridge method estimates the above equation and the respective values of parameters, obtaining estimates of residues of the model, $\Delta\hat{\boldsymbol{\varepsilon}}_{it}$. If the model errors are not serially correlated, then $Corr(\Delta\boldsymbol{\varepsilon}_{it}, \Delta\boldsymbol{\varepsilon}_{it-1}) = -0{,}5$. This involves regressing the results of residues of the first equation with its lagged values and verify if parameter associated with the lag is statistically equal to $-0{,}5$. The test applied is robust in relation of the presence of conditional heteroscedasticity. Finally, to test for autocorrelation in the OLS pooled method, it was used the method proposed by Cumby and Huizinga (1992) under the null hypothesis of no serial autocorrelation of the first order.

In presence of serial autocorrelation and heteroscedasticity, variance-covariance matrix of the parameters was corrected using the broker from White (1980) with grouped residues (cluster) by cross section (firm). The two procedures are intended to ensure estimators HAC[i]

4. Analysis of Results

4.1. Descriptive analysis of data

In this section, firms were classified in three groups: sectors with high-intensity of R&D, sectors with medium-intensity of R&D and sectors with low-intensity of R&D. This conceptualization was adopted in accordance to the report criteria, following definition:

Table II: Definition of sectors per degree of intensity in R&D.

Group of sectors	**Intensity in R & D (R & D / Sales)%**
High-intensity	> 5%
Medium intensity	[1%, 5%]

[i] For more details on the HAC estimators class, see Newey and West (1987).

Low-intensity	<1%
Definition of sectors	
High-intensity	Pharmaceuticals & biotechnology; Health care equipment & services; Technology hardware & equipment; Software & computer services and Aerospace & defense.
Medium intensity	Electronics & electrical equipment; Automobiles & parts; Industrial engineering & machinery; Chemicals; Personal goods; Household goods; General industrials; Support services. Food producers; Beverages; Travel & Leisure; Average; Oil equipment; electricity; Fixed line telecommunications.
Low-intensity	Oil & gas producers; Industrial metals; Construction & materials; Food & drug retailers; Transportation; Mining; Tobacco; Multiutilities.

Source: Adapted from The 2013 EU Industrial R & D Investment Scoreboard, 2013 [p.27].

Table III shows the distribution of companies according to the three groups of sectors defined in Table II.

Table III: Distribution of firms by groups of intensive sectors in R&D.

Industry group	**Freq. Abs.**	**Freq. Rel. (%)**	**Freq. Accum. (%)**
High-intensity	202	3.35	3.35
Media-intensity	1,367	22.68	26.03
Low-intensity	4,459	73.97	100.00
Total	**6028**	**100.00**	-

Source: developed by the authors.

According to table III, the smallest proportion of firms is distributed to the high-intensity group, with 3.35% of the sample, compared to 22.68% on average-intensity and a greater proportion of low-intensity firms, with 73.97%. This pattern reveals an asymmetry with great performance of firms with low intensity of R&D.

Table IV: Distribution of firms by type of efficiency.

Industry group	**Freq. Abs.**	**Freq. Rel. (%)**	**Freq. Accum. (%)**
efficient firms	1,692	28.07	28.07
inefficient firms	4336	71.93	100.00
Total	**6028**	**100.00**	-

Source: developed by the authors.
Note: The definition of the firms follow the criteria established in the methodology for efficient firms and inefficient firms. Thus, the efficiency parameter takes values in the restriction. $\theta(x,y) = 1$ (efficient firms); $\theta(x,y) < 1$ (inefficient firms) $\leftrightarrow \theta(x,y) \leq 1$

According to Table IV, the efficient firms account for approximately 28% of the sample compared to 72% of inefficient firms. The following table 'crosses' the distribution of firms by efficiency and intensity of group research.

Table V: Distribution of firms according to type of efficiency and intensity group.

Type firms	**Freq.**	**Types of intensity in R & D**			**Total**
		High	**Average**	**Low**	
	Abs.	26	309	1,357	1,692
efficient	Rel. Line (%)	1.54	18.26	80.20	100.00
	Rel. Column (%)	12.87	22.60	30.43	28.07
ineffective	Abs.	176	1,058	3102	4336

	Rel. Line (%)	4.06	24.40	71.54	100.00
	Rel. Column (%)	87.13	77.40	69.57	71.93
	Abs.	**202**	**1,367**	**4,459**	**6028**
Total	**Rel. Line (%)**	**3.35**	**22.68**	**73.97**	**100.00**
	Rel. Column (%)	**100.00**	**100.00**	**100.00**	**100.00**
Pearson chi2 (2) = 55.6678 / p-value = 0.000					

Source: developed by the authors.
Note: The definition of the firms follow the criteria established in the methodology for efficient firms and inefficient firms. Thus, the efficiency parameter takes values in the restriction.$\theta(x, y) = 1\theta(x, y) < 1\ \ \theta(x, y) \leq 1$

Based on the table above, the distribution of efficient firms has a higher proportion of low intensity research group (80.2%) versus a smaller proportion of high strength (1.54%). The same pattern is also observed for inefficient firms, where the largest proportion is concentrated in low-intensity companies (71.54%) against 4.06% in the proportion of firms with high intensity. Comparing between the three intensity research groups, the proportion of inefficient firms overcomes efficient firms in relatively close values. Finally, the chi2 test showed a significant association between the factors ('efficiency' versus 'sector group').

4.2. Results of the econometric model

Table VI shows the results of econometric model shown in ME.1 equation, according to each estimation method illustrated above.

Table VI: equation results me.1

VARIABLES	(1) Fixed Effects Robust	(2) Random Effects	(3) OLS Pooled robust
log(R&D)	0.205***	0.154***	0.0751***
	(0.0357)	(0.0144)	(0.0150)
log(R&D)*$\theta_{it}(x, y)$	0.00955***	0.0399***	0.131***
	(0.00363)	(0.00429)	(0.0114)
log(K)	0.116***	0.311***	0.488***
	(0.0316)	(0.0121)	(0.0287)
log(L)	0.261***	0.465***	0.391***
	(0.0643)	(0.0173)	(0.0389)
Constant	4.288***	1.277***	1.268***
	(0.589)	(0.171)	(0.236)
Fixed Effects			
Firm	yes	-	-
Year	yes	-	-
R^2	0.9975		0.938
Heteroskedasticity test	2.8e+30		0.04
p-value	0.0000		0.8346
Autocorrelation test	71.482		516.769
p-value	0.0000		0.0000
Sargan-Hansen statistic	228.618		
p-value	0.0000		
F statistic	35.64		2112

p-value	0.0000		0.0000
chi2		5739	
p-value		0	

Source: developed by the authors.
Note: (§) each autocorrelation has a distinct distribution pattern. (A) statistical Wooldridge (2002) follows a statistical F while (B) cumby and Huizinga (1992) follows a chi-square distribution.
The asterisks *, **, *** represent significance levels 10%, 5%, 1%, respectively. The 'robust' term implies that the results reported in the table was proceeded correction of the variance-covariance matrix using the estimator White (1980) grouped with waste per cross section. In this case, the estimator reported belongs to the class of the Best Linear Unbiased Estimators - BLUE.

According to the model results, the coefficient of elasticity from investments in research showed a significant increase comparing different methods, suggesting that OLS pooled technique underestimates its value to disregard the influence of fixed effects (0.2 for fixed effects from 0.075 for OLS and 0.15 for random effects, a variation of 167% for the first case and 33% for the second one).

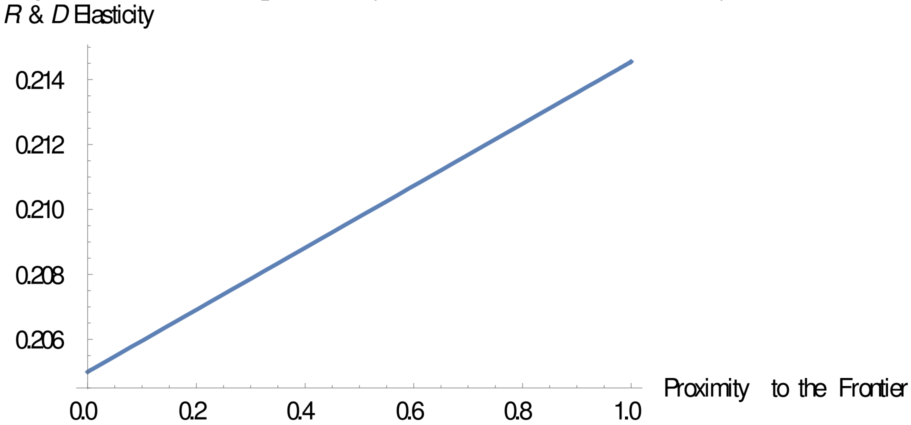
Regarding the coefficient linked to the efficiency score, it was observed a decrease comparing the OLS pooled method with random effects and fixed effects. This aspect indicates an overestimate when the effects of heterogeneity of the sample are excluded from the main model. Comparing the method of fixed effects with random effects, the reduction of the parameter represents a variation of approximately 92%. Comparing efficient firms, the coefficient of final elasticity is 0.206% for OLS pooled and 0.215% for fixed effects (what represents an increase of 4%). We could also observe that both the capital and labor elasticity coefficients showed a significant reduction when comparing the methods of fixed effects, random effects and OLS.

Regarding the heteroscedasticity tests, the results showed a significant presence in the model of fixed effects (rejection of the null hypothesis of homoscedastic residue at 1%), unlike the method OLS pooled (non-rejection of the null hypothesis at 10%). Rather, autocorrelation tests showed evidence of autocorrelated residues in both models, rejecting the null hypothesis at the 1% level.

The Sargan-Hansen statistical presented a very high value (chi2 = 228.618), rejecting the null hypothesis at 1%. It indicates that the fixed effects showed significant correlation with the regressors of the model. Thus, deleting them in the stochastic error would be an error of specification, what could induce regressors to problems of endogeneity and, therefore, the bias in parameters. This bias is illustrated in overestimation of the parameters of capital and labor and underestimation of investments in research.

Figure 1 shows the effect that the proximity to the frontiers promote in the final coefficient of elasticity of R&D. Using a simulation based on the results of the fixed effects model, it is evident that the most efficient firms have higher elasticity coefficients of R&D. These results are consistent with the theoretical model presented and recent researches on this field (Coad (2008; 2011), Kancs and Siliverstovs (2016) and Montresor and Vezzani (2015)).

Figure 1: Effects of proximity to the frontier on elasticity, Fixed Effects.

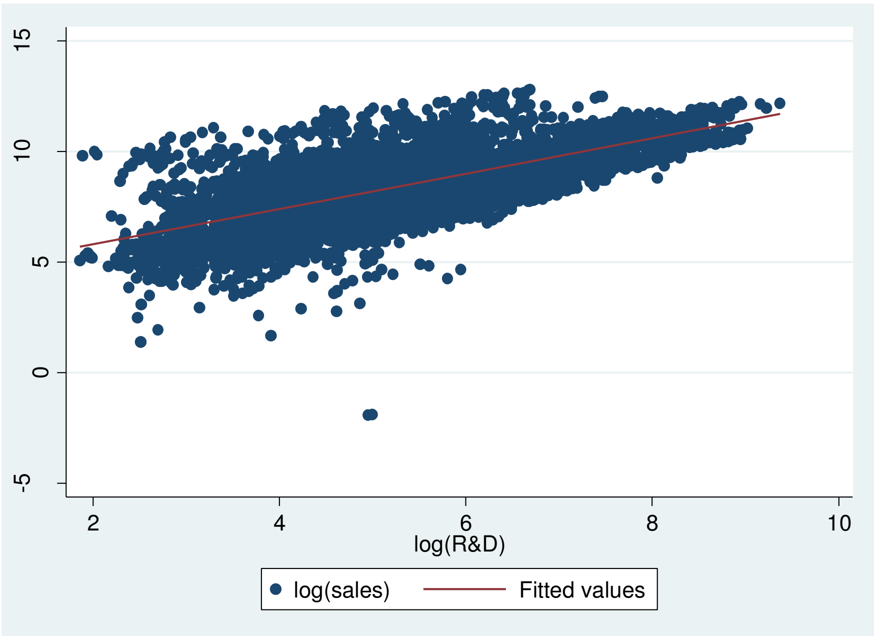


Source: developed by the authors.

Note: The elasticity coefficient was obtained from the partial derivative of me.1 equation related to investments in R&D, $\epsilon^{R\&D} \equiv \frac{\partial log(y_{it})}{\partial log(R\&D_{it})} = \hat{\beta}_1 + \hat{\beta}_2 * \theta_{it}(x,y)$.

Figure 2 shows the relationship between R&D and sales through the scatter plot. The estimated line is reported in order to assess the degree of dispersion of data around the average. Points above and below the line can be illustrated in the model through the efficiency coefficient, which creates different 'weights' in the relation between variables.

Figure 2: scatter plot, log (sales) x log (R&D).



Source: developed by the authors.

4.3. Discussion of the results with recent research

Recent studies have shown that distance to the frontiers can influence in different contexts of investments, especially highlighting 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 frontiers employ R&D resources more efficiently, generating significantly higher scores than the more distant firms.

As Hölzl and Janger (2014), perceived barriers to innovation is statistically higher for firms present in economies more distant from technological frontier. In this sense, at the same way that the percentage of innovative companies decreases with distance to the frontier, the relative number of companies that do not see importance to innovation increases.

The results corroborate with those presented evidence, since the most efficient firms and possibly operative in 'real' technology frontier demonstrate to use the R&D with greater leverage on the return in sales. This aspect may be related to the nature of the investment, since this can be more connected to the factors responsible for displacement of the frontiers. Thus, the furthest firms may have opportunity costs in the use of such investments, so that the eficient use of resource can be lower in relation to firms loccated on the frontier.

5. Final Considerations

Through the quantile regression technique, Coad and Rao (2008) show that the innovativeness index, created by the authors, through the crossing of series of investments in R&D and patent stocks, is crucially important for firms with highest growth in sales. Thus, firms located in the upper tail of the conditional distribution of sales growth obtain greater return from innovation applied by the firm. Although the present research had employed an isolated measure of "innovation effort" - investments in R&D -, the authors conclude that this procedure is still consistent with the findings in their research, demonstrating the importance for the analysis of the topic. This positive association between investments in R&D and sales was also presented in Coad and Rao (2010a).

However, R&D investments not only have a heterogeneous effect on the growth rate of sales, but have recently been pointing to their influence on the variance of the growth rate. It indicates that such investments are influenced by risks and uncertainties, demonstrating that advances in these studies are still inconclusive. Thus, the results of this research help to fill these gaps, indicating that the proximity to the border has a positive and superior impact in firms closer to the technological frontier, corroborating with the findings in researches that used different econometric techniques.

Interacting the calculated scores with investments in R&D, the results showed that the elasticity coefficients of firms on the frontier were significantly higher compared to inefficient firms. Controlling model through the effects of heterogeneity of the sample (fixed effects), the results showed gains that can be expressed as an increase in the elasticity coefficient of approximately 4% compared with the model that excludes it. These results can support important decisions in policies of Science & Technology, since the differences reflected between efficient and inefficient firms point to different results in the use of investments. This suggests that a policy implemented in the frontiers economies can not lead the same results in less developed economies.

The conclusions of the study point to a strong influence of the factor proximity to the frontier in the return of investments in R&D. These results suggest that this pattern may reflect important differences between countries. Other studies, especially Acemoglu, Aghion and Zilibotti (2006), Aghion and Howitt (2009), Aghion et al. (2014), Aghion, Howitt and Prantl (2015) and Aghion and Festré (2017), among others, have pointed out that the economic performance of a country varies according to its proximity to the technological frontier, demanding a set of policies with different intensities, according to their position. These aspects were adequately discussed at firm-level in Coad (2008, 2011), but with a different treatment by the present research. The different techniques involved between the studies fortify their conclusions, converging the results to a more uniform consensus and adherent to the Schumpeterian theory.

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Appendix A

Operationalization of variables

The variables provided in this study were collected in the report. The definitions and metrics involved in each variable catalog are presented below:

(i) **Investments in Research and Development (R&D)**: It is represented for all expenditure directed to research, defined as activities conducted to develop new knowledge, whether directly related to scientific or technical level. The development perspective involves the application of resources for the production of new goods or substantially improved, devices, products, processes, systems or services. These investments are expressed in millions of euros.

(ii) **Investment in capital assets (capex)**: It is represented for the expenditure realized by companies, focusing to acquire or upgrade physical assets such as equipment, property or industrial buildings. On the account of 'capital expenditure' is added to the asset account (i.e. capitalized), increasing the basis of the asset. Therefore, it is the tangible fixed assets of the companies. These investments are expressed in millions of euros.

(iii) **Liquid sales**: It corresponds to the accounting definition of sales, excluding sales tax and participations in sales as joint venture and shareholders. For banks, sales are defined as total operating income plus income from insurance. In relation to insurance companies, the sales are defined as gross premiums written plus any other banking products.

(iv) **Number of employees**: It is represented by the annual average number of employees or in the results presented at the end of the fiscal year.

(v) **Profitability**: It is the ratio between operating profit and liquid sales. Operating profits, in turn, are obtained "(...) the profit (or loss) before taxation, plus net interest cost (or minus net interest income) minus government grants, less gains (or plus losses) Arising from the sale / disposal of businesses or fixed assets " (EUROPEAN COMMISSION, 2014, p.105). Values are expressed in percentage units.

(vi) **Intensity of investments in capital assets (capex intensity)**: It is ratio between investments in capital goods and sales. Values are expressed in percentage units.

Appendix B

Free Disposal Hull

The advantages of this technique of efficiency scores can be described, as shown below:

(i) Non-parametric techniques, unlike the parametric assumptions, do not depend on the functional form of the production function and axioms statistical in process of data generator, making them more attractive for estimating factors or scores associated with efficiency (Badin, Daraio and Simar, 2014);

(ii) There are two important methods in the non-parametric technique:

(2.1) DEA method, where the firms' production set takes the assumptions of free disposal (or waste of potential in resources) and convexity (Florens, Simar, and Keilegom, 2014). This approach has been widely used since the contributions of Charnes, Cooper and Rhodes (1978). However, problems associated with the indivisibility of inputs and products, economies of scope and scale, as well as factors associated with specialization, make the assumption of convexity rather weak, leading efficiency scores bias problems in the presence of such 'anomalies' (Daraio and Simar, 2007).

(2.2) In violation of convexity, a robust technique becomes more appropriate in the estimation of efficiency scores: Free Disposal Hull or FDH. This technique, based on contributions from Deprins, Simar and Tulkens (1984), consists in a more general version of the DEA estimator, including the assumption of Free Disposal in the set of production and relaxing the assumption of convexity. This has become the most attractive FDH technique in studies of effectiveness.