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Full Research Article

Corporate R&D and the performance of food-processing firms: Evidence from Europe, Japan and North America

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Abstract. This paper investigates the impact of corporate research and development (R&D) on firm performance in the food-processing industry. We apply Data Envelopment Analysis (DEA) with two step bootstrapping using a corporate data for 307 food-processing firms from the EU, US, Canada and Japan for the period 1991-2009. The estimates suggest that R&D has a positive effect on the firms' performance, with marginal gains decreasing in the R&D level as well as the performance differences are detected across regions and food sectors. R&D investments in food processing can deliver productivity gains, beyond the high-tech sectors generally favoured by innovation policy.

Keywords. Corporate R&D, DEA, double bootstrapping, food-processing industry.

JEL codes. O30, L66.

1. Introduction

Both the theoretical and empirical literature established that R&D is critical for firm productivity growth. For example, the empirical literature has found that between 1% and 25% of variance in the actual productivity across firms can be explained by differences in R&D investment (Hall *et al.*, 2010). However, there is considerably less agreement on the size of the R&D impact on the firm's productivity (e.g. the size of marginal impact, diminishing vs. increasing returns to R&D).

Existing analysis of the implications of R&D mainly focus on knowledge-intensive businesses; there are less studies covering R&D and innovation in low- medium-tech sectors such as food-processing. The literature is highly scattered in the field of agro-food sector ranging from conceptual analysis, system-oriented approach analysis (e.g. Jongen and Meulenberg, 2005; OECD, 2012, 2013) to public R&D in agro-food sector (Alston,

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2010). Analyses on public R&D and its impact on primary agriculture production are more numerous given that the relevant data is more accessible. Conversely, much less effort has poured into the private R&D even though it probably represents the largest share of the overall sector's R&D (e.g. 59% in Japan, 51% in US according to Alston *et al.* 2010). Furthermore, the firm level studies seldom focus on specific aspects of R&D (e.g. adoption, product variety). Most are case studies with a limited regional or sectorial coverage (e.g. one country, part of the sector). Broader quantitative analyses are limited by data measurement and availability constraints.

The food-industry is usually considered to be a medium to low R&D intensity sector representing around 0.27 % of the total output in the EU agro-food industry (FoodDrinkEurope, 2015) compared to other sectors such as the automobile (5.5%) or pharmaceutical (13.1%) industries (Hernández *et al.* 2015). This is understood, among others, to be related to the fact that the agro-food sector is dominated by SMEs which do little research, many innovations are often derived from other input sectors and thus are incorporated in machinery, packaging and other manufacturing supplies (e.g. Menrad, 2004) as well as many food-products are rather easy to imitate with significant R&D spillovers which reduces firms' incentive to invest in R&D (Gopinath & Vasavada, 1999).

Although this general patterns may hold, the agro-food industry shows a high heterogeneity in the R&D intensity (Avermaete *et al.*, 2003; Winger and Wall, 2006; Feigl and Menrad, 2008; Capitanio *et al.*, 2010). There is a strong geographic heterogeneity in the level of private R&D. Heterogeneity is also present in the type of innovation among firms: process, product, or organisational innovation. Finally, it is important to mention that firms also differ whether they invest in R&D externally or internally.

The objective of this paper is to contribute to this literature by providing empirical evidence on the impact of private (corporate) R&D on productivity of food-processing firms. More specifically, we analyse the size of firm inefficiency and explore the determinants of the inefficiency against the frontier production function using a unique corporate data set of food-processing firms from the EU, US, Canada and Japan for the period 1991-2009. To derive productivity parameters, we apply Data Envelopment Analysis (DEA) with two step bootstrapping which allows us to correct the bias in (in)efficiency and generate unbiased estimates for (in)efficiencies.

2. Methodology

To estimate the impact of private R&D on firm productivity we adopt a two-step approach. First, we use DEA to estimate firm performance (inefficiencies). Second, we run regression to explain the determinants of firm inefficiencies on a set of explanatory variables including private R&D.

Different approaches have been applied in the literature to identify production frontiers using both parametric and non-parametric methods. Here we adopt a non-parametric approach - DEA with two step bootstrapping (Simar and Wilson, 2007). The advantage of DEA is that it does not require imposing assumption on the functional form of the frontier, there are no restrictions regarding the number of parameters required, it is relatively easy to deal with a whole range of inputs and outputs, and inputs and outputs can have very different units. However, in general, some limitations remain in terms of considering time series, sensitiveness to outliers, demanding to incorporate (nonparametric) statistical inference, etc.

Methodologically, however, the assumption of a common frontier across countries and sectors is a sensitive issue potentially leading to biased results (Koop *et al.*, 2000; Limam and Miller, 2004; Orea and Kumbhakar, 2004). This paper avoids assuming a common technology across sectors by estimating at industry-specific technology level.

A frontier production function, in general, defines the maximum output achievable, given the current production technology and available inputs. We estimate DEA model in the formulation of output distance function:

$$\hat{\delta}_i = \delta_i(\mathbf{X}, \mathbf{Y} \mid T) = \max\left\{\delta > 0 \mid \delta \mathbf{y_i} \le \mathbf{Y}\lambda, \mathbf{x_i} \le \mathbf{X}\lambda, \mathbf{i'}\lambda = 1\right\} \tag{1}$$

where δ_i is inefficiency parameter of firm i, y_i is output; δy_i is maximum output achievable (frontier), x_i and X are inputs; λ are weights used to construct the virtual producer (frontier). The main idea of DEA is to find virtual firm (combination of other firms) capable of producing more output for the given inputs.

In the second stage, the inefficiency parameters are regressed on a set of explanatory variables, z_i, to estimate the determinants of inefficiency:

$$\delta_i = \mathbf{z_i}\beta + \varepsilon_i \ge 1 \tag{2}$$

where β are parameters to be estiamted and ε_i is an independent and identically distributed (i.i.d.) error term.

For estimation, δ_i has to be replaced by $\hat{\delta}_i$ (the estimated efficiency scores from the first stage):

$$\hat{\delta}_i = \mathbf{z_i}\beta + \xi_i \ge 1 \tag{3}$$

Usually a Tobit regression is applied to estimate the parameters of β. This procedure become necessary because the error term e_i is truncated and not symmetrically distributed with mean zero. Examples of the z variables – and as such also used in this study – are R&D intensity, capital intensity, time, country dummies (capturing different institutional settings), etc.

Simar and Wilson (2007) point to several problems with this approach and advocate for the use of a truncated regression, instead. The $\hat{\delta}_i$ are serially correlated in an unknown way since each $\hat{\delta}_i$ depends on all observation in T. Thus the δ_i are not independent of each other which induces biased estimates in the second step since the usual assumption regarding the error term does not hold.

Moreover, since x_i and y_i are correlated with z_i (otherwise the second step would make no sense), z_i is correlated with ξ_i. The correlation disappears asymptotically, however, at a very slow rate.

As a solution to this bias they suggest a two-step bootstrap algorithm (Simar and Wilson, 2007). First, we correct the bias in (in)efficiency (in DEA). Second, we get unbiased estimates for (in)efficiencies (in the truncated regression). That is, the bootstrap allows to bias-adjust coefficient estimates and also for calculating proper confidence intervals for the statistical inference.

Bootstrapping tends to affect the structure of the data, potentially generating other forms of bias through an 'over-manipulation' of the data. A possible alternative is to develop an instrumental variable to control for the bias. However, this alternative was not seen as operational taking in consideration the available data.

3. Data and variables

Considering strengths and limitations of several potential sources of data,[1] Standard & Poor's (S&P) COMPUSTAT data set (S&P, 2014) was favoured which contains data at firm level collected from companies' audited annual/quarterly reports.

The selection process of firms from the available population of companies entailed several steps. The first consisted in retrieving firms classified as belonging to agriculture (industry code: 0xxx) as well as those to the food-industry (industry code: 2xxx); covering the period 1991-2009. Data had to cover revenue, sales, net income, capital and R&D expenditures (if any); number of employees and/or wage sum, industry code, and region/country (i.e. info on the location of the company's headquarter/where it is registered). However, as most companies from agriculture did not report R&D expenditures, they were dropped from the final sample.

Labour input is critical when considering firm performance. In the case of missing 'number of employees' but available labour expenditures, the number of employees was approximated by using average wage levels taken from International Labour Organisation (ILO) and for values of labour costs vice versa.

The dataset does not allow distinguishing whether R&D was conducted domestically or abroad. All companies' R&D expenditure was assigned to the country where the company is registered.

The DEA approach applied in this paper is sensitive to outliers. Moreover, presuming a common production frontier for companies across countries implicitly assumes that all companies have access to the same technology and produce under virtually the same technological restrictions. Hence, reducing the sample to a sub-sample comprising of rather homogeneous countries/companies appeared advisable in order to ensure widely unbiased empirical results. Outlier observations, however, still need to be excluded from the sample.

After carrying out a final outlier check (checking for consistency and order of magnitude across observations as well as along the time series) some further firms/observations had to be dropped. Thus, outliers were excluded based on the results of Grubbs' tests centred on the sectoral average growth rates of firms' R&D stock intensity (K/revenue) over

[1] For instance, the AMADEUS database may contain sufficient cross-section and time series firm level data, but provides information on R&D (if at all) only for very recent years. The presumed emergence of the food-processing sector as medium-tech, evolving from formerly low-tech, could not be investigated accordingly based on such data. Another possible source of data could be the EU Industrial R&D Scoreboard (released by EC Joint Research Centre). This database comprises of fully consolidated firm level data of top R&D investors in Europe and elsewhere (year of last audited report + 3 years back in time). However, among the listed companies, there are too few belonging to the food-industry.

the investigated period.[2] Moreover, some further observations were dropped for reasons related to the computation of the R&D and capital stocks.

In accordance with the literature (see Hulten, 1991; Jorgenson, 1990; Hall and Mairesse, 1995; Bönte, 2003; Parisi *et al.*, 2006), stock indicators (rather than flows) were used as impact variables. It is thus implicitly assumed that a firm's productivity is affected rather by the cumulated stocks of capital and R&D expenditures and not only by current or lagged flows.[3] Accordingly, our main impact variable is a firm's R&D stock (K) and the second impact variable is 'capital expenditures' (C) captured as capital stocks. By considering the per capita values of these variables (i.e. per number of employees), it allows us both to standardise the data and to eliminate firms' size effects (see, for example, Crépon *et al.* 1998). In this framework, knowledge (R&D) and physical capital stocks were computed using the perpetual inventory method based on the following formulas:

$$K_{t0} = \frac{R\&D_{t0}}{g_{s,c}(K)+\delta} \tag{4}$$

$$K_t = K_{t-1} \cdot (1-\delta) + R\&D_t \text{ with t = 1991, … , 2009} \tag{5}$$

$$C_{t0} = \frac{I_{t0}}{g_{s,c}(C)+\phi_j} \text{ and} \tag{6}$$

$$C_t = C_{t-1}(1-\phi) + I_t \tag{7}$$

where *R&D* is R&D expenditure and *I* is gross investment (capital expenditure).

The OECD ANBERD and the OECD STAN databases were used to provide growth rates $g(K)$ and $g(C)$ for K and C, respectively. We computed the compounded average rates of change in R&D and fixed capital expenditures in the food-processing sector and per country (c). For some European countries the mentioned databases did not report or allowed calculating specific growth rates for R&D- and capital-stocks. The corresponding European averages were assumed in these cases instead. For the US, Canada, and Japan, however, the growth rates were taken from the literature.[4]

In general, different depreciation rates (δ) and (ϕ) for K and C should be assumed depending on whether the industry is high-, medium-high, medium-low/low-R&D intensity. In fact, more technologically-advanced sectors are characterised (on average) by short-

[2] Grubbs' test – also known as maximum normalised residual test – assumes normality (which is a desirable property anyway). Accordingly, we ran normality tests on the relevant variables (assumption was never rejected).

[3] Using cumulated R&D and capital stocks – as in the previous relevant literature – overcomes a potential endogeneity problem which can arise if flows are used.

[4] For capital growth from OECD (Capital Services, total; mean percentage change 1985-2009; see: http://stats.oecd.org/Index.aspx) and for R&D growth rates the average over the period 1980-1998 was taken from (http://www.ulb.ac.be/cours/solvay/vanpottelsberghe/resources/DGBVP_OES.pdf

er product life cycles and by a faster technological progress which together accelerates the obsolescence of the current knowledge and physical capital. In this light, Ortega-Arquiles *et al*. (2009) suggested sectoral depreciation rates of 20%, 15% and 12% to the knowledge capital and 8%, 6% and 4% to the physical capital respectively for the high, medium-high-, and medium-low/low-tech sectors, with the latter (δ=12%, ϕ=4%) to be applied here to the food-processing industry. These are similar to the 15% and 6% commonly used in the literature (Musgrave, 1986; Nadiri and Prucha, 1996; Pakes and Schankerman, 1986; Hall, 2007).

All variables in monetary units were transformed into 2007 Euro using the end of year exchange rate. In cases where no direct exchange rate to Euro was provided by COMPUSTAT, for a certain year, the corresponding currency was transferred into USD first and then into Euro.

After processing the data, the sample used in this paper consists of 307 companies (2948 observations) for the period 1991-2009 registered in either of the following country groups: EU (557 observations), North America (USA and Canada, 1,050 observations), and Japan (1,341 observations), as shown in Table 1.

Europe is less represented than Japanese and North-American counterparts. There is no information on Japanese firms prior to 1999 and most regions are less represented for this period. However, the period starting in 2000 is more balanced, including for Europe. To control for this data structure we use a dummy variables in our estimations to distinguish these two periods.

As shown in Table 1, there is observed significant heterogeneity among the 307 firms. The mean number of employees varies between 2211 in Japan to 15293 in the EU. Nev-

Table 1 Descriptive statistics of main variables

Variable	Mean	Std. Dev.	Min	Max	Firms	Obs.
Total sample					307	2948
Revenue	2308.3	5192.3	0.4	51514		
COGS-costs	1443.5	3295.6	0.4	47137		
R&D expenditure	89.7	451.7	0	7290.3		
Capital expend.	1286.4	2996.3	0	25846		
Employees	10610	31443	2	486000		
EU companies					85	557
Revenue	2705.8	6602.6	0.4	51514		
COGS-costs	1561.2	3323.9	0.4	22873		
R&D expenditure	175.6	926.9	0	7290.31		
Capital expend.	1768.9	4020.4	0	25846		
Employees	15292.7	36441.3	2	269000		
US & Canada					79	1050
Revenue	3684.8	6607	1.7	50659		
COGS-costs	2309.5	4578.3	1	47137		
R&D expenditure	72.5	266.4	0	2476		
Capital expend.	1839.9	3584.2	0	24759		
Employees	18054	43375	2	486000		
Japan*					143	1341
Revenue	1065.3	1983.5	5	15913		
COGS-costs	716.6	1330.7	2	9785.7		
R&D expenditure	67.5	181.5	0	1642.2		
Capital expend.	652.6	1497.7	0	13127		
Employees	2211	4203	16	36554		

*(1999-2009 period only)

ertheless, in each macro region, apparently, there are also a number of small and even micro-companies. It has to be stressed that the final sample gathers rather large companies, inherent with stock listed company data. This entails that results cannot be easily generalised as rather small private companies operating in the food-processing sector are not captured, but should be considered pertinent to large firms which, in fact, are inclined to be more active in terms of R&D. Also, this kind of "pick the winner" effect might be particularly severe in medium and low-tech sectors (like food-processing), where the overall company population tends to be dominated by smaller firms which scarcely engage in R&D investment (Becker and Pain, 2002).

The sample mean of R&D-intensity (R&D/sales) is above 1% in all macro-regions with the EU reporting the highest rate (~6%). This would allow classifying the companies/sector as medium-tech (even medium-high), according to the commonly applied classification (Hatzichronoglou, 1997). Considering the median R&D-intensity rather than the mean, the R&D/sales ratios do not change significantly in magnitude in Europe and the US/Can, but they drop below 1% in Japan. However, in the EU and the US/Can only a few firms perform R&D at all (but those which do, however, have significant spending), while in Japan most companies are engaged in R&D activities but modestly at individual level.

In general, the companies active in the food-processing sector in the EU and in the US/Can seem to be fairly similar: EU companies are, in average, a little smaller in terms of revenue (sales) and number of employees but have almost exactly the same ratio of net income/revenue as those from US/Can and also comparable figures in terms of spending on R&D and capital (including their accumulated stocks). In contrast, Japanese firms appear smaller and less profitable, more inclined to do corporate R&D, but, in average, at a lower financial (Table 1). These differences between macro regions need to be taken in consideration when interpreting the estimated results and performing cross-country comparisons.

In terms of sub-sector representation, observations from beverages companies are the most present followed by mixed-activity or generalist food-processing firm and prepared foods, accounting for 53% of the total sample. The remaining subsectors account individually between 4% and 9% the dairy sub-sector which is marginally present in the sample (Table 2).

Table 2 Sample composition - observations per subsector

Subsector	Codes	No. observations
Beverages, including alcohol	2080-2087	561
Mixed/generalist	2000	490
Prepared foods	2090-2099	491
Meat and poultry packing	2010-2015	272
Sugar and confectionery	2060-2068	252
Canned fruits and vegetables	2030-2038	225
Grain	2040-2048	226
Bakery	2050-2053	197
Dairy	2020-2026	18
Oils	2070-2079	116
Total		2948

4. Results

4.1 The size of inefficiency

An output-oriented efficiency model (variable returns to scale-VRS) was run with a simple specification made of one output and three inputs. Inputs consist of capital stock (*C*), labour (number of employees, *E*) and total cost of goods sold (*COSD*). The output was measured as the value of total revenues assumed to be total food related sales, although firms may have sales revenue from other lines of activity and streams of income such as asset management (Fuglie *et al*., 2011).

The distribution of efficiency scores by frequency is displayed in Figure 1. In general, the figure shows that the inefficiency distribution is skewed to the left indicating that most of the companies operate relatively close to their frontier (panels b and c). Very high inefficiencies could only be found for a few companies. Moreover, panel (a) shows an estimate of the bias of the inefficiency estimate. The distribution reveals that the bias is considerable. Thus conducting an analysis without bootstrapping would have led to largely biased estimated parameters in the second step. Panel (b) gives an example of the inefficiencies calculated with the adjusted technology *T**. Finally, panel (c) give the unbiased estimator (distribution) of the inefficiency.

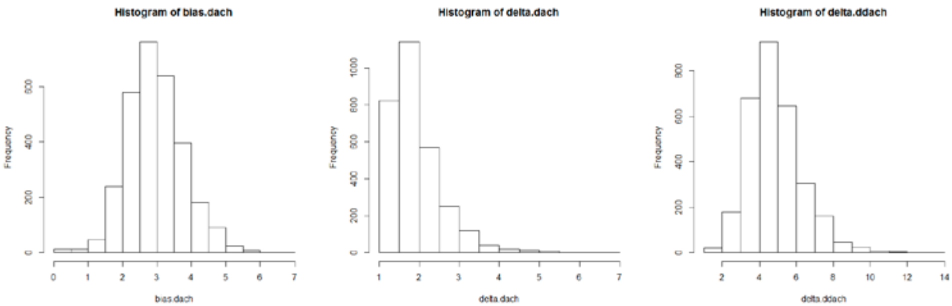
4.2 The determinants of inefficiency

The basic hypothesis of the second stage is that R&D has a positive impact on firm performance. In general, the determinants of inefficiency will be captured by the knowledge base of a company which depends on (a) on own R&D and (b) knowledge created elsewhere (universities, research institutes, companies) and diffuses to the public domain.

The main objective of this paper is to capture the effect of the first type of knowledge. As a result, we include the variable own (private) R&D expenditure of companies

Figure 1. Illustration of inefficiency estimates and estimated bias, frequencies.

(a) (b) (c)



Inefficiency units | Inefficiency units | Inefficiency units

$BI\hat{A}S(\hat{\delta}_i) = BIAS(\hat{\delta}_i) + v_i$ | $\hat{\delta}_i^* = \delta(\mathbf{x}_i, \mathbf{y}_i \,|\, T^*)$ | $\hat{\hat{\delta}}_i = \hat{\delta}_i - BI\hat{A}S(\hat{\delta}_i)$

(without distinguishing whether it is internal or external R&D) in the set of explanatory variables (z) considered in the second stage estimations. Usually the information is available when the companies are required to publish their investments. Although it can be safely assumed that large companies in all countries have some R&D, however, they have no spontaneous incentive to report it since this would reveal information about the firm's strategy and threaten the firm's competitive position.

This lack of data may bias the result. However, no information on R&D is less severe than expected. Given the basic hypotheses, the impact of R&D on performance might be less significant since firms which do not report but conduct research should be more efficient than expected.

Regarding the knowledge created elsewhere (technological opportunities), firm R&D impacts not only the revenues directly but in addition also affects the technological opportunities of the firm. The firm's technological opportunities consist of two parts: the knowledge external to the sector (universities, public research institutes) and the existing knowledge at the competitors which diffuses to some extent into the public domain (Cohen and Levinthal, 1989). The degree of openness depends on the institutional regulations regarding the protection of firm specific knowledge but also from the type of technology.

The use of public knowledge depends on the absorption potential. This absorption depends on the height of the R&D expenditure as well the characteristics of the scientific and technological foundations. In addition it is determined by the ease how this knowledge can be absorbed.

In order to account for differences in the knowledge and research infrastructure we consider regional dummy variables in the estimation. We expect that the US and Japan have a favourable knowledge base to conduct R&D and this knowledge base also finds its expression in better firm performance. Some indication of this can be seen Table 1 which shows that Japan and the US have the highest research expenditures related to outputs. The same effect can be expected for the old EU Member States ("EU15"). Similar to Japan and the US, they belong to the group of countries with a highly developed research infrastructure. Given the structural difficulties of EU New Member States ("NMS") from Eastern Europe in particular related with their past history of planned economy, the research systems in these countries are likely less developed thus attaining lower productivity levels. The reference region for these regional dummy variables is Canada. Note that, some studies find that Canada reports lower performance of food-processing firms than their peers from other developed countries such as US (Chan-Kang *et al.* 1999; in Fuglie *et al.* 2011)

To further control for the knowledge and research infrastructure beyond the regional dummies, the contemporaneous general public R&D investments per capita is also introduced in the regression (GERD of government sector, Euros equivalent, 2007 constant prices).

The time lags and dynamic effects (e.g. see Andersen & Song, 2013) are not controlled for in the analysis, given that the availability of data in the sample for different years varies strongly across firms and regions. However, to account for the differences in the sample structure over time, dummy variables are used for the 1990s period and the period 2004-2009 with the 2000-2004 period serving as reference.

Table 3. Truncated regression estimates of the determinants of efficiency.

Independent variables	1A (biased)	1A	1B	2A	2B	3A	3B	4A	4B	5A	5B
Constant	*2,2880*	5,7321*	5,7437*	4,9921*	5,0246*	5,9101*	5,7705*	5,7044*	5,8331*	5,9844*	6,0773*
R&D, perpetual inventory	*-0,8243*	-0,7931*	-1,0606*	-0,8684*	-1,1703*	-0,6639*	-0,9157*	-10,7639*	-10,8921*	-0,9767*	-1,1729*
(R&D, perpetual inventory)^2			0,0447*		0,0532*		0,0386*		0,1176*		0,0810*
GERD, gov. sector/ capita	*-0,0023*	-0,0026*	-0,0028*	-0,0040*	-0,0041*	-0,0062*	-0,0054*	-0,0052*	-0,0057*	-0,0063*	-0,0066*
Japan	*-0,7098*	-0,9469*	-0,9248*			-1,2181*	-1,1465*	-1,1878*	-1,2033*	-1,2020*	-1,2328*
USA	*-0,7378*	-1,0090*	-1,0082*			-1,0157*	-1,0204*	-1,0542*	-1,0579*	-1,1013*	-1,1263*
EU12, NMS	*0,9666*	1,6572*	1,6479*			1,4837*	1,5142*	1,4666*	1,4820*	1,5267*	1,6351*
EU15	*-0,2256*	-0,2823*	-0,3052			-0,5035*	-0,4022*	-0,4321*	-0,3465*	-0,4832*	-0,5173*
1990s dum.	*0,1187*	0,1938*	0,1852*	0,2708*	0,2827*	0,0904	0,1029	0,0904	0,0768	0,0861	0,0790
After 2004 dum.	*0,2399*	0,2815*	0,2763*	0,3897*	0,3990*	0,1697*	0,1843*	0,1781*	0,1808*	0,1950*	0,1965*
Dairy				0,3069*	0,3273*	-0,0636	-0,0556	-0,0901	-0,1270	0,1876	0,2057
Canned				0,1105	0,1026	0,2952*	0,2545*	0,2593*	0,2313*	0,2500*	0,2280
Beverages				-0,5804*	-0,5828*	-0,7585*	-0,7190*	-0,7069*	-0,7598*	-0,7698*	-0,7936*
General				0,1760	0,1583	0,1551	0,1461	0,1676*	0,1292	0,1108	0,1826
Meats				0,3146*	0,2854*	0,4265*	0,3832*	0,4036*	0,3487*	0,6228*	0,6248*
Oils				-0,5020*	-0,5396*	-0,3130*	-0,3251*	-0,2887*	-0,3198*	-0,0022	-0,0199
Bakery				0,3042*	0,2958*	0,4644*	0,4124*	0,3915*	0,3527*	0,4686*	0,4696*
Prepared foods				0,3893*	0,3919*	0,4236*	0,4049*	0,3870*	0,3786*	0,3461*	0,3603*
Sugar				-0,1587	-0,1696	-0,0466	-0,0952	-0,0758	-0,0792	0,0155	-0,0030
Japan x R&D								10,2002*	9,9897*		
USA x R&D								10,1015*	9,8361*		
(EU12, NMS) x R&D								-0,2317	-0,5675		
EU15 x R&D								9,9956*	8,7063*		
Dairy x R&D										-1,5265*	-1,5851*
Canned x R&D										-0,1390	-0,0883
Beverages x R&D										0,2183	0,1948
General x R&D										0,1830	-0,4624
Meats x R&D										-9,0025*	-9,1332*
Oils x R&D										-4,4689*	-4,5715*
Bakery x R&D										-0,8573	-0,8754
Prepared foods x R&D										0,5644*	0,4738*
Sugar x R&D										-1,2186*	-1,1682*

NMS: EU New Member States. * indicates stat. significance at 5%. Source: own calculations on R v2.14 with FEAR package.

The estimated results of the second stage pooled truncated regression are reported in Table 3. We have estimated several alternative and complementary model specifications to avoid potential collinearity between explanatory variables. Model 1A starts with a simple specification of the estimated equation which includes private R&D (perpetual inventory), public R&D (GERD/per capita), time dummies, and regional dummies (US, Japan, EU, etc.) with Canada serving as the reference country. For comparison purposes, we also report the results obtained with the biased estimators for the first model (1A biased). The remaining models are only presented with their unbiased estimators. The extended first model (1B) also considers squared value of private R&D with the aim to capture the change in marginal gains from additional investment in private R&D.

The second set of models (2A, 2B) considers sectoral dummies instead of regional dummies with firms specialised in grain processing being used as the reference sub-group. Model 2B expands 2A with adding squared value of private R&D. The third set of models (3A and 3B) add both regional and sectoral dummies in the estimated equation. Again, model 3B expands 3A with adding squared value of private R&D.

The remaining model sets (4 and 5) consider interaction variables between private R&D and regional and sectoral dummy variables, alongside the variables considered in the first three model sets, in order to capture whether the impact of private R&D vary across regions or sectorial circumstances, respectively. That is, the fourth set of models (4A, 4B) includes interaction variables between private R&D and regional dummies, while the fifth set of models (5A, 5B) interacts private R&D and sectoral dummies.

The estimates largely confirm the hypothesis that private R&D has a positive effect on performance (i.e. it reduces inefficiency) of the food-processing firms (Table 3). However, the variable controlling for marginal gain of additional investment does systematically capture decreasing marginal returns of R&D investments on performance at firm level. Public R&D has also statistically significant contribution to performance, in line with country specific studies such as for the Spanish food sector by Acosta *et al* (2015). However, the relationship is complex as hinted by Maietta *et al* (2017) whose analysis of the R&D sector in Europe over the 2007-2009 period suggest a displacement effect on *intra-muros* (internal) R&D by government R&D. These results are consistent across all estimated models.

Private R&D investing seems to more positively affect performance in Canada (the reference country) than in the USA, Japan or EU15 countries (4A and 4B). The estimated coefficient for new EU member states is not significant in both models where the interaction variables between private R&D and regional dummies are considered (i.e. 4A and 4B). These results suggest that additional R&D investment in Canada and NMS would produce greater firm efficiency gains than in in the USA, Japan or EU15. With regards to sub-sectorial sensitivity to R&D investment on firm performance (5A and 5B), some sub-sectors (dairy, meat processing, oils and sugar) seem to be more responsive to R&D investment and statistically significant compared to the reference sector (grain). In contrast, processed food sectors are less sensitive to R&D investment, while the remaining sub-sectors were found to be statistically insignificant relative to the reference sector.

The performance of food-processing firms during the period after 2004 is significantly lower compared to the 1990s and especially compared to the reference period (2000-2004). In terms of regional variation of firm performance, the estimates suggest that Japanese, US, and EU15 firms are more efficient that Canadian firms which corroborates with previous studies comparing US and Canadian firms (Chan-Kang *et al.* 1999, Fuglie *et al.* 2011). The food-processing firms from the NMS tend to underperform the Canadian peers, and hence the firms from other countries.

Firm operating as generalist of the food-processing sector tend not to indicate a statistically significant difference with the reference group (grains). In most models, this is also the case for dairy and sugar-related firms, while for oil and canned producers the results are mixed in terms of statistical significance. However, firms specialised in meats, bakery and prepared foods tend to be less efficient than those involved in grains; these resulte are statistically significant across all models.

5. Conclusions

This paper confirms the hypothesis that R&D investment influences firm performance: food-processing firms which invest in R&D tend to be closer to the efficiency frontier compared to those that do not invest in R&D (i.e. private R&D has a negative effect on inefficiency). Estimates of this paper also point to decreasing marginal returns in reducing (increasing) inefficiency (efficiency) by private R&D as well as that that the general public R&D has a positive effect on efficiency of food-processing firms.

When looking at the drivers of firm performance, country/region dummies do capture differences and similarities in knowledge systems and nature of the sector. Similarities can be detected in the US and Japanese contexts. Further, as expected, less favourable eastern European (NMS) context is indentified in the estimated results as compared to the performance of firms from old EU Member States. However, the results suggest that gains from additional investment in R&D could be greater in NMS than old EU Member States or the US.

The findings of this paper have to be considered, however, with some caution on the account of the data limitations. The persistent lack of reporting R&D in certain countries in the EU may create biases in the estimated effects. Further, the sample contains rather larger firms from the food-processing industry (a key factor determining R&D, as illustrated by Acosta *et al* (2015) for the Spanish food sector), while small firms are underrepresented. This data limitation does not allow to fully extrapolate the results obtained in this paper to the whole food-processing industry.

Overall, the results of this paper show that R&D in food-processing industry is associated with higher firm performance. At the same time, the sample used in this paper includes medium-high-tech (and larger) food-processing firms, questioning the generally held view on the sector as being rather low-tech. By prioritising high-tech sectors, emerging technologies, knowledge-based services, etc., the current backbone of the European economy, mainly constituted by industries that are often rather medium- and even low-tech, tend to be somewhat marginalised from the policy attention perspective (Hanse and Winther, 2011). Results of this paper show that growth opportunities could also be expected and encouraged from this type of non-high-tech innovative sectors. Further, the results of this paper suggest heterogeneity in R&D effects across EU Member States, hence innovation policies may have different implications across EU regions.

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7. Disclaimer

The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

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