European Commission

JRC TECHNICAL REPORTS

The impact of private R&D on the performance of food-processing firms

Evidence from Europe, Japan and North America

Task 4.4 report

Pedro Andrés Garzón Delvaux, Heinrich Hockmann, Peter Voigt, Pavel Ciaian, Sergio Gomez y Paloma

2018

The Impact of Research on EU Agriculture

impresa

Joint Research Centre

EUR 28249 EN

Contact information
Name: Sergio Gomez y Paloma
Address: Edificio Expo – Inca Garcilaso, 3, E-41092 Seville – SPAIN
E-mail: Sergio.GOMEZ-Y-PALOMA@ec.europa.eu
Tel.:+34 954 48 83 58

JRC Science Hub
https://ec.europa.eu/jrc

JRC104144

EUR 28249 EN

PDF ISBN 978-92-79-63972-2 ISSN 1831-9424 doi:10.2788/85468

Luxembourg: Publications Office of the European Union, 2018.

How to cite: Garzon Delvaux, P.A., Hockmann, H., Voigt, P., Ciaian, P. and Gomez y Paloma, S., The impact of private R&D on the performance of food-processing firms: Evidence from Europe, Japan and North America. Report to the FP7 IMPRESA project. EUR 28249 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-63972-2, doi:10.2788/85468, JRC104144.

Table of contents

Acknowledgements

We thank our IMPRESA consortium partners for their comments during the development of the project. Special thanks go to Davide Viaggi and Michele Vollaro for the review of a previous version of the report.

Our thanks also go to our colleagues Mark Boden, Andrea Conte and Pietro Moncada Paternò Castello from JRC Unit B3 Territorial Development (former Knowledge for Growth Unit) for having first described and then provided access to the Compustat database relevant to our analysis. We express our appreciation to our former colleagues Marianne Lefebvre and Sébastien Mary who initiated the IMPRESA project at the JRC. Thanks to the team at PrePress Projects for revising the English.

Finally, we acknowledge the funding received for this project from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement No 609448.

The impact of private R&D on the performance of food-processing firms: evidence from Europe, Japan and North America

Pedro Andrés Garzón Delvaux[1], Heinrich Hockmann[2], Peter Voigt[3], Pavel Ciaian[1], Sergio Gomez y Paloma[1]

[1] Joint Research Centre (JRC), European Commission
[2]Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)
[3]Directorate-General for Economic and Financial Affairs (DG ECFIN), European Commission

Abstract

This report investigates the impact of corporate research and development (R&D) on firm performance in the food-processing industry. The agro-food industry is usually considered to be a low-tech sector (the share of total output that is attributable to R&D is around 0.27% in the EU). However, the agro-food industry is very heterogeneous. On the one hand, there are many highly innovative food-processing firms with intensive R&D activity and, on the other hand, many food-processing firms derive and adopt innovations from other sectors such as machinery, packaging and other manufacturing suppliers. We perform 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. We use a corporate dataset of 307 companies from agriculture and food-processing industries from the EU, the USA, Canada and Japan for the period 1991–2009. The estimates suggest that R&D has a positive effect on firms' performance, with marginal gains decreasing at the R&D level, and performance differences detected across regions and food sectors. General public expenditure in R&D is also associated with a positive impact on firm performance. As a result, policy support for this type of non-high-tech innovative sector is expected to generate growth. However, results that suggest heterogeneity in R&D effects across EU Member States may point to differences in the implications of innovation policies across EU regions.

Keywords: Research and development, corporate R&D, productivity, technical efficiency, stochastic frontier analysis, DEA, double bootstrapping, agro-food, food-processing industry

Executive summary

This report was produced as part of the **Impact of Research on EU Agriculture (IMPRESA)** project. The aim of the IMPRESA project is to measure, assess and comprehend the impact of all forms of European scientific research on agriculture (SRA) on key agricultural policy goals, including farm-level productivity, environmental enhancement and the efficiency of agro-food supply chains.[1]

In the framework of the IMPRESA project, this report investigates the impact of corporate research and development (R&D) on firm performance in the food-processing industry. Productivity growth in agriculture and the food industry is a key element in responding to the challenges of global food security. As such, investment in R&D and innovation is critical to promoting productivity gains in the agro-food sector.

Both the theoretical and empirical literature has established that R&D is critical for firm productivity growth in general. For example, according to the empirical literature, between 1% and 25% of variance in 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 impact of R&D on firms' productivity (e.g. diminishing vs. increasing returns). A case in point is the magnitude of the estimated marginal impact of R&D, which ranges from highly negative to highly positive, while many studies do no not find any statistically significant results.

Existing analyses of the implications of R&D mainly focus on knowledge-intensive businesses; there are fewer studies covering R&D and innovation in low- or medium-tech sectors such as food processing. Studies on R&D in primary agricultural production (e.g. genetically modified organisms (GMOs), yield productivity) are more common.

The literature in the field is highly scattered, from conceptual analysis and system-oriented analysis (e.g. Jongen and Meulenberg, 2005; OECD, 2012, 2013) to public R&D in the agro-food sector (Alston, 2010). Analyses of public R&D are more numerous given that the relevant data are more accessible (e.g. Eurostat, Organisation for Economic Co-operation and Development (OECD) Structural Analysis Database (STAN), Agricultural Science and Technology Indicators (ASTI)). However, much less effort has poured into private R&D, even though it probably represents the largest share of the sector's overall R&D (e.g. 59% in Japan and 51% in the USA, according to Alston et al., 2010).

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 sectoral 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 an industry with medium- to low-intensity R&D: the share of total output that is attributable to R&D is around 0.27% in the EU (FoodDrinkEurope, 2015), which is significantly lower than in other industries such as the automobile (5.5%), software (10.6%) or pharmaceutical (13.1%) industries (European Commission, 2015). This is understood to be related to the fact that research activities in many food companies play a minor role or are simply not carried out at all. Many innovations are derived from other input sectors and thus are incorporated in machinery, packaging and other manufacturing supplies (e.g. Menrad, 2004). In addition, the agro-food sector is dominated by small and medium-sized enterprises (SMEs), which do little research.

Small (marginal) innovations are prevalent among agro-food firms (as opposed to the 'radical' new technological developments in high-tech industries). Moreover, most food products are rather easy to imitate, with significant R&D spillovers, which reduces firms'

---

1 http://www.impresa-project.eu/objectives.html

incentive to invest in R&D – innovators have difficulties internalizing (capturing) returns from investments (Gopinath and Vasavada, 1999).

That said, the agro-food industry is very heterogeneous (Avermaete et al., 2003; Winger and Wall, 2006; Feigl and Menrad, 2008; Capitanio et al., 2010). There is geographical heterogeneity, for example firms in the Netherlands or Finland spend a significantly higher percentage of output on R&D than their Italian or French counterparts (OECD STAN; FoodDrinkEurope, 2015 (2012 data)). In turn, some firms in the sector are simply innovative and active in R&D. There is also heterogeneity in terms of the type of innovation: process, product or organizational innovation. Finally, it is important to mention that firms may invest in R&D either externally or internally.

Testing the impact of R&D on the performance of agro-food-processing firms involves several methodological challenges. The first, a recurrent challenge, concerns data: there are issues associated with availability, short time series, changing definitions of R&D, breakdowns by type of R&D and disclosure of sensitive firm-level R&D information. Agreement on basic measurements of R&D and the consistency of data sources remain a challenge.

A second challenge is linked to the difficulties in successfully capturing the time dynamics (i.e. lag effects) of R&D. The time lag between R&D activity and commercialization is particularly problematic for firm-level R&D: usually only short temporal resolution is available for firm-level data. This contrasts with the 35- to 50-year lag for public R&D in the USA (Alston et al., 2010).

A crucial challenge is that of attributing firm performance to R&D. Identifying the share of a firm's performance that is attributable to its own R&D, to other firms' R&D (spillover effect) or to public R&D is problematic. Moreover, the analysis needs to identify the type/component of R&D that has affected firm performance (e.g. process vs. product vs. organizational innovation).

Analysts also need to account for spatial and spillover effects of R&D (e.g. intra-/inter-country and firm spillover effects).

In this context, and using a unique corporate dataset of 307 companies from agriculture and food-processing industries from the EU, the USA, Canada and Japan for the period 1991–2009, we analyse the magnitude of inefficiency and explore the determinants of inefficiency for each firm against the frontier production function, which defines the maximum output achievable. 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.

Our sample, although mainly consisting of large firms, suggests that segments of the food-processing industry can be considered to be sectors with medium- to high-intensity R&D, in contrast with the generally held perception that the food-processing industry is a low-intensity industry for R&D.

Data show that EU firms tend to be slightly smaller in terms of revenue, sales and number of employees than their North American competitors. However, they have a similar ratio of net income/revenue and R&D expenditure as firms from the USA/Canada. In contrast, Japanese firms appear smaller, less profitable and more inclined to carry out corporate R&D but, on average, with less financial investment.

Our main results confirm the hypothesis that investment in R&D influences firm performance: food-processing firms that invest in R&D tend to be closer to the efficiency frontier than those that do not (i.e. private R&D has a negative effect on inefficiency). At firm level, the results also point to decreasing marginal returns to private R&D. Furthermore, the results show that general public expenditure in R&D is also associated with a positive impact on firm performance.

When looking at the drivers included in the analysis, country/region dummies capture differences and similarities in knowledge systems and the nature of sectors. Similarities can be detected between the US and Japanese contexts. A less favourable eastern European context is identifiable from the exercise. Compared with western EU Member States, food-processing firms in new EU Member States underperform. However, additional R&D investment in new Member States would produce greater firm efficiency gains than in the other countries of the sample.

Data availability, as also highlighted by the literature, remains a main constraint, preventing in-depth and more nuanced analysis of the implications of R&D on firm performance.

The results of this exercise provide only an overview of the links between R&D and performance. Such exercise precludes decomposing the impact of the structure and type of R&D on firm performance (e.g. process vs. product vs. organizational innovation; external vs. internal research).

The deviations or inefficiencies that the model is expected to capture are key to the analysis because this is the indicator of performance causally linked to R&D investments. With DEA and the estimation of the production frontier, all deviations from the frontier are attributed to the inefficiency term, whereas some of them could also be due to noise, which is difficult to distinguish from the prime effect under scrutiny.

Going into greater detail entails greater heterogeneity (type of R&D, inputs–outputs) coupled with scarcer data. In turn, additional details make the analysis more complex and, in particular, less adapted to quantitative approaches such as sector-wide DEA. If greater detail and focus are required, narrower industry and/or case study approaches are more suitable than broad quantitative approaches.

From a policy perspective, the results suggest that growth opportunities could be expected and encouraged from this type of non-high-tech innovative sector. However, results that suggest heterogeneity in R&D effects across EU Member States may point to differences in the implications of innovation policies across EU regions.

Introduction

Productivity growth in the agro-food industry is a key element in responding to the challenge of global food security. As such, investment in research and development (R&D) and innovation is critical to productivity in the agro-food sector. This is being pursued through innovation policy with initiatives such as the Business and Industry Advisory Committee (BIAC) of the Organisation for Economic Co-operation and Development (OECD), which, following a study on innovation and food security (OECD, 2009), concluded that innovation to address global food security challenges needs to be prominent in the OECD Innovation Strategy. Moreover, the OECD Agriculture Committee is encouraged to consider fostering innovation in the agro-food sector as a long-term issue to be reflected in any future work programme, and to help governments, portraying an objective picture of the various challenges and opportunities that exist in this area (see OECD, 2009, p.6). In 2010, the EU launched the Europe 2020 Strategy to create conditions for smart, sustainable and inclusive growth (European Commission, 2010). The 'smart' component of the strategy aims at effective investments in education, research and innovation. The priorities in such investments are particularly shaped by budgetary austerity, which also affects private investments.

Investments in R&D, financed by both public and private funds, are at the core of the innovation process. However, while the theoretical links between inputs and outputs of the innovation process are quite clear, the causal relationships between investments and broader measures of technological change – encompassing frontier technologies affecting industry dynamics, growth, productivity and competitiveness of companies and entire sectors – are rather complex in practice.[2]

The **Impact of Research on EU Agriculture (IMPRESA)** project aims to measure, assess and comprehend the impact of all forms of European scientific research on agriculture (SRA) on key agricultural policy goals, including farm-level productivity, environmental enhancement and the efficiency of agro-food supply chains.[3]

In the framework of the IMPRESA project, this report sheds light on the role and impact of R&D on company performance in the food-processing industry.

The food-processing sector can hardly be labelled 'high-tech' or 'emerging' in the sense of being characterized by outstanding growth patterns. However, there is evidence of its moderate growth track. Setting aside high-tech emerging technologies, Europe relies economically on more established, 'traditional' sectors. The food-processing industry, though already partly in transition, is one of these traditional sectors.

In this light, the relationship between R&D activities in the agricultural and food-processing industries and firm performance is investigated. This report is designed to provide answers to the following two main research questions:

- Is corporate R&D a driver of firm performance in sectors commonly characterized as medium- or low-tech, such as food processing?
- Regarding food-processing firms, is there a significant difference in corporate R&D investment between the EU, the USA/Canada and Japan?

In other words: can this be a basis for R&D policy-making? If so, where (e.g. low-, medium- or high-intensity R&D food-processing firms; small-, medium- or large-scale firms) can the highest marginal effects of investing in R&D be found (i.e. where does corporate R&D pay off the most)? By answering these questions, we attempt to identify a potential target group for R&D/industry policy within the food-processing industries.

---

2 The need for a better understanding of these relationships is particularly reinforced in the context of the Europe 2020 strategy, with a strong emphasis on leveraging productivity and innovativeness.

3 http://www.impresa-project.eu/objectives.html

This report is organized as follows. The next section, Section 2, presents a synthesis of the existing literature on R&D (and corporate innovation activities)[4] in agriculture and food-processing industries and the available empirical evidence. Section 3 develops an empirical model and the results estimated using corporate data on 307 companies from agriculture and food-processing industries in the EU, the USA, Canada and Japan for the period 1991–2009. Section 4 concludes with a discussion of the results and policy implications. Section 5 focuses on the methodological lessons learned from the exercise, including its limitations and the challenges in interpreting the results.

R&D in the agro-food industry: a review

1.1. R&D and the performance of firms

Theoretical relationships between investments in R&D and the output of the innovation process are fairly well understood. However, the empirical connections between R&D inputs and their effects on the productivity, growth and competitiveness of firms (and sectors) are complex and difficult to apprehend.

Griliches (1958) paved the way for a remarkably large body of literature dealing with such links. Private R&D investment as a primary source of firm productivity growth is well established in the literature.[5] However, there is considerably less agreement on the marginal impact of R&D on a firm's productivity. Both diminishing returns to R&D (Corsino et al., 2011) and increasing returns to R&D (Cohen and Klepper, 1996a,b) have been reported in the literature. The estimated marginal impact of R&D ranges from highly negative to highly positive and many studies do not find any statistically significant results. Reviews on the issue point to the underlying theoretical framework as a key source of variation in these results (Hall et al., 2010; Hall and Rosenberg, 2010).[6]

The traditionally used knowledge capital model of Griliches (1979) has several important drawbacks (as outlined by Griliches (1995, 2000)). Of particular concern are two of the model's assumption: (i) a linear accumulation of knowledge in proportion to R&D expenditures, which is, moreover, often combined with the assumption of linear depreciation when constructing the stock of knowledge capital (Hall, 2007); and (ii) homogenous firms with the same R&D expenditure should have the same productivity. Both assumptions are questionable given the uncertain outcomes of individual research efforts (e.g. the non-linear relation between spending on R&D and outcomes).

Most literature focuses on knowledge-intensive businesses. Relatively low-tech sectors, such as agriculture or agro-food, have attracted less attention, especially when looking at the specific role and impact of R&D and innovation on agriculture and food processing

4 Note that in the literature R&D and innovation are sometimes used synonymously but sometimes denote different types of activities. R&D without a direct link to product/process innovation (e.g. investigating biochemical processes in organisms, decoding DNA of certain parasites relevant for plant or animal production) is fundamental rather than applied research. Although arguably relevant for agriculture and/or the food-processing sector, such activities are not commonly associated with these sectors, at least not in terms of innovation. Hence, they are not considered here. Moreover, since the focus of this study is corporate R&D activities, innovation without R&D is not captured here either (except where stated otherwise).

5 See the exemplary Hall and Mairesse (1995). Note that this understanding corresponds to the widely applied knowledge capital model (Griliches, 1979), which has since developed in many directions (see Griliches (1995) for a comprehensive overview). For instance, Pakes and Schankerman (1986) modelled the creation of knowledge by specifying a production function in terms of R&D capital and R&D labour. Jaffe (1986) initiated ways of accounting for the appropriability of the external flows of knowledge or spillovers. For more recent examples see Griffith et al. (2004, 2006).

6 For the current understanding of and some of the open debates about the role of R&D and innovation in economic growth, see Fagerberg et al. (2004).

and – in particular – on related business sector R&D activities. In fact, in this regard, the literature appears to be somewhat scattered.[7]

1.2. Nature and magnitude of the sector

The agro-food industry is usually considered to be an industry with relatively low-intensity R&D: the share of output that is attributable to R&D investment is estimated to be 0.27% in the EU (FoodDrinkEurope, 2015), which is significantly lower than in other industries such as the automobile (5.5%), software (10.6%) and pharmaceutical (13.1%) industries (Hernández et al., 2015). These figures support the 'traditional' perception of the food industry as a low-tech sector (e.g. Christensen et al., 1996; Grunert et al., 1997; Garcia-Martinez and Burns, 1999; Garcia-Martinez and Briz, 2000; Christensen, 2008).[8]

However, for several years this economic sector has, on the one hand, been undergoing technical and economic changes in the production and processing of food and, on the other hand, increasingly responded to consumers' demand for improved environmental protection, animal welfare, food quality and safety standards. Examples include new scientific and technical approaches in food processing, responses to food scares or scandals and socio-demographic developments (Menrad, 2004). Thus, innovation as an element of competition between companies in the food industry is growing in importance (Grunert et al., 1997) as it becomes increasingly important for companies to stand out from competitors and fulfil consumer expectations (Menrad, 2004). Hence, figures on innovation activities and/or R&D spending at aggregated sector level and company level, benchmarking of innovative activities and some empirical analyses of R&D in food processing have become increasingly available in the literature.[9]

Corresponding evidence suggests that the impact of R&D and innovation as performed by food-processing firms goes well beyond the sector. For instance, Ghazalian and Furtan (2007) investigated the effect of innovation (and implicitly R&D) on primary agricultural and processed food product exports among the OECD countries.[10] R&D capital stock was thus employed as a tangible way of measuring innovation.[11] Empirical results suggest that R&D has different effects across sectors. In particular, the authors found that R&D has a net positive market expansion effect on exports of primary agricultural products because a 10% increase in R&D capital induces a 7.9% increase in exports. However, the authors highlighted that in the food-processing sector, in contrast, the market expansion effect of R&D appears to be more than offset by the market power

---

7 Admittedly, hundreds of studies have been published reporting measures of agricultural productivity, the effects of R&D on agricultural innovation and productivity patterns – for example, the resulting social payoffs for investments in agricultural R&D. However, in comparison with corresponding studies investigating other economic sectors, the body of literature on agro-food businesses still appears comparably small and thematically non-exhaustive.

8 For an overview of thresholds and a brief discussion, see: www.oecd.org/dataoecd/32/17/41419823.ppt.

9 For comprehensive empirical data (at aggregate level), see, for example, OECD online data sources: Innovation in science, technology and industry – Research and Development Statistics (RDS) (<link>); or the corresponding tables available from Eurostat: Science and Technology – Research and Development (<link>). Company-level data can be obtained, for instance, from Standard & Poor's Capital IQ Compustat database (<link>), Bureau van Dijk's Amadeus <link> or – to a limited extent – the EU Industrial R&D Investment Scoreboard provided by the European Commission (<link>). A further source frequently used for innovation studies is the European Community Innovation Survey (CIS) (several waves) (<link>). See the exemplary Batterink et al. (2006) for a study of the agro-food sector based on CIS data.

10 Most agricultural R&D studies have focused on estimating the domestic effects of agricultural R&D (e.g. Alston et al., 1995; Huffman and Evenson, 2006a). In contrast, Ghazalian and Furtan (2007) investigated the benefits of agricultural R&D at international level (both directly through primary agricultural exports and indirectly through enhancements of agro-food exports).

11 The empirical exercise uses panel datasets covering 21 OECD countries for the period 1990–2003. A theoretical gravity equation that accounts for innovation is derived.

effect (i.e. R&D in the food-processing sector induces firms to increase their mark-ups), resulting in an overall decrease in export volumes. However, in the same study, evidence of a positive vertical channelling effect was found, through which R&D in the primary agricultural sector tends to increase exports of related processed food products. In other words, the role and ultimate economic impact of R&D and innovation at sector level is non-trivial, especially regarding the interplay with downstream and closely related and/or vertically integrated businesses.

General information and empirical studies on the sectoral trends of food-processing industries and the corresponding role of R&D are presented by, for instance, FoodDrinkEurope (2015).[12] Accordingly, global trends in R&D investment in food processing suggest recently sustained levels. The world's top 61 leading food and drink companies collectively invested €8.7 billion in R&D in 2012. Out of these 61 companies, 17 are based in the EU and invested €2.3 billion in 2012.[13] FoodDrinkEurope suggests that the EU food and drink industry, compared at aggregate level, has a lower R&D investment level than other food and drink industries worldwide.[14] Furthermore, R&D investment levels also vary within the EU, with higher expenditures in northern European countries following the general pattern of R&D investments in the respective countries (with the exception of the UK). The 2015 EU Industrial R&D Investment Scoreboard (Hernández et al., 2015) shows that Germany, the Netherlands and the Scandinavian countries have a total R&D intensity of around 4%, whereas Italy's is below 2% and France's is around the EU average at just below 3%. These data could be influenced by the importance of a few sizeable but low-intensity sectors such as oil and gas production and banking (e.g. in the UK).

1.3. Drivers and types of R&D in the sector

The literature offers avenues to understand, on the one hand, the low R&D spending in the food industry[15] and, on the other, the drivers that can act as incentives for R&D and particular types of R&D.

Research activities still play a minor role in most food-processing companies and in some cases are not carried out at all. Furthermore, as argued above, many innovations are derived from other input sectors and are incorporated in machinery, packaging and other manufacturing supplies. The same applies to the producers of food ingredients, which often belong to the chemical industry (see, for example, Menrad, 2004). For the same reasons, the number of innovations (in terms of new products) in the food industry is comparatively high considering the low R&D spending.

Arguably, another potential explanation for the low R&D expenditure is that small and medium-sized enterprises (SMEs), which constitute the majority of enterprises in the

---

12 Brussels-based international sector association: http://www.fooddrinkeurope.eu/about-us/role-and-mission/

13 Distribution of the 17 EU food and drink companies: NL, 5; UK, 4; DE, 3; FR, DK, FI, BE and IE, 1.

14 According to the World Bank's World Development Report 2008, developing countries invest only a ninth of what industrial countries put into agricultural R&D as a share of agricultural GDP (World Bank, 2008, p.34). It is further noted that investments in agricultural R&D have turned much of developing-world agriculture into a dynamic sector, with rapid technological innovation accelerating growth and reducing poverty (World Bank, 2008, p.179ff).

15 For instance, Wilkinson (1998) presented an early study concerning R&D priorities of leading food-processing firms and analysed a range of literature dealing with the issue of innovation in agro-food, focusing in particular on the dynamics of R&D. He discussed the view that low levels of internal R&D among the sector's leading firms, when compared with chemicals or pharmaceuticals, are consistent with strategies devoted primarily to superficial product innovation. Against such an interpretation, the author presented arguments that point to a systematic long-term effort towards increasing control over the biological processes that lie at the heart of the food industry on the basis of intersectoral technology flows. In the light of these considerations and the emergence of significant in-house research activity by leading agro-food firms, the article concludes with an appreciation of the way in which the industry is responding to the challenges and opportunities of advances in biotechnology.

food industry, often do not allocate adequate personnel and financial resources to R&D activities (Schmalen, 2004). This is remarkable given that, as outlined by Avermaete et al. (2003), R&D and innovation in food processing is particularly relevant, especially for small firms in the sector.[16] In fact, although the agro-food sector is perceived to be a rather low-intensity R&D sector overall, this perception is not accurate for all businesses operating in the sector and also ignores stark regional differences, as illustrated in Table 1. In fact, the corresponding evidence suggests that the relevance of R&D and innovation activities for food processing differs across countries and regions, and especially if compared firm by firm (Dutta and Lanvin, 2013). This is highlighted by Feigl and Menrad (2008) in a TRUEFOOD[17] project report, which presents the results of a study on innovation activities in food-processing industries in selected European countries. The authors investigated R&D and innovation in food-processing industries in Italy, Germany and the UK and, in particular, the types of companies that invest in R&D and innovation (how much/with what R&D intensity) differentiated by country and size (SMEs vs. larger enterprises).

Table 1 Corporate R&D investment in the food and drink industry: companies in the EU Industrial R&D Investment Scoreboard (2013) listed among the world's top 2,000 companies, 2012

	R&D investment (€ billion)	**Share of R&D investment by world regions (%)**	**Number of companies listed**
USA	2.9	33.1	15
EU	2.3	26.7	17
Japan	1.8	20.8	23
Switzerland	1.4	16.1	2
New Zealand	0.2	1.9	1
South Korea	0.1	1.4	3
Total	8.7	100	61

Source: European Commission (2013)

However, several drivers are also pushing for more R&D in this industry. The main objectives of R&D emerge as either product innovation or process innovation (to raise the productivity of inputs). Furthermore, organizational innovation leads to organizational changes to firms' business and marketing practices and market and organizational strategies. Although there is no systematic record of the actual focus of R&D investments, existing analysis suggests that most investments are allocated to product innovation rather than cost-saving processes or organizational innovations (Fuglie et al., 2011).

16 Weindlmaier (2001) underlined the decisive role of R&D spending in SMEs for their future competitiveness. See also Baregheh et al. (2012) who analysed innovation in food sector SMEs in the UK by means of a questionnaire-based survey, exploring specifically the degree and types of innovation employed, specific activities concerning the general focus of innovative activities and organizational innovativeness.

17 TRUEFOOD (traditional united Europe food) was a project funded by the Sixth Framework Programme (FP6) of the European Commission. The project aimed to introduce an innovation perspective into the traditional European food production systems. See: https://cordis.europa.eu/project/rcn/79816_es.html

Fortuin and Omta (2009) investigated the main drivers of and barriers to innovation in agro-food and the extent to which the food-processing industry can rely on the principles of innovation management developed in high-tech industries. Based on data obtained from questionnaires (completed by Dutch multinational food producers at CEO level), it appears that the general lessons and principles of innovation management do apply and that, more specifically, the uneven power distribution in value-added chains and retail chains (especially high pressure from buyers) acts as a strong driver of innovation in agro-food businesses. For most of the companies, the authors observed remarkable room for improvement in the communication between marketing and R&D divisions in order to enhance customer orientation, identified as one of the main drivers of the sector's innovation success.

In light of such a demand-driven pull for food product innovations, Winger and Wall (2006) analysed R&D and the character of food product innovations. The authors describe the food industry as being one in which there are a large number of new products offered to retailers each year, and the inclusion of a new product almost always leads to the discontinuation of another product. However, the authors point out that only a very small proportion of new products appear to result in radical changes. The majority reflect incremental changes (i.e. they reflect the 'D' of R&D).[18] In addition, about 75% of new products were considered to be failures.[19] In the USA, 21,000 or so new food products are introduced each year and 90% are not classified as innovative (USDA/ERS, 2010) and have a short effective market life. It was noted by the authors that in comparison with other industries (e.g. electronics, biotechnology) there is a low level of R&D in the food-processing sector given the relevance of technology and machinery and the constant pressure to develop new products and product innovations.

Patents and formal protection of intellectual property does not significantly influence innovation in the food sector in the USA, as highlighted by Gopinath and Vasavada (1999). The short market life of most food-industry innovations and the pervasiveness of product imitation deter patent registration. Moreover, the spillover effects of process innovation contribute to the underinvestment in this innovation opportunity by food-processing firms reinforcing the importance of product innovation over process innovation investment in this sector (Gopinath et al., 2003).

Capitanio et al. (2010) looked at product and process innovation exclusively in the Italian food industry. The authors pointed out that innovation – whether process, product or organizational – is perceived as a strategic factor for firms and for the entire sector.[20] The authors base this conclusion on the observation that R&D and innovation allow a reduction in production costs and/or an improved response to the needs of consumers, who increasingly require 'enhanced' food products with service components and technological processing characteristics such as quality, safety, ease of use and storability.

Beckeman et al. (2013) investigated how food-producing companies in Sweden perceive R&D and innovations, how they view their role and those of other actors regarding innovation activities in the food supply/value chain and what this implies for their

---

18 There are several systems for classifying food products by innovation. The innovation spectrum is described using terms such as 'new to the world', 'product improvements' and 'cost reductions'. Innovations can also be described as leading to incremental, major and radical changes. See Winger and Wall (2006) for a discussion and further details.

19 Similar figures are confirmed by Loizou et al. (2013) who investigated variables that influence the adoption of food product innovations and modelled the corresponding consumer behaviour. In particular, a two-step cluster analysis was employed to explore various levels of differentiated product adoption and a categorical regression model was estimated to explain this variation. The study relied on a survey of 500 consumers, conducted in 2009 in a Greek urban area.

20 In another study of the Italian food sector, Capitanio et al. (2009) highlighted that the adoption of innovations apparently follows different patterns for product and process innovation. The probability of introducing product innovation is influenced by the quality of human capital, the geographical context and, to a lesser extent, the age of the firm.

interaction and collaboration.[21] The authors confirmed that few (if any) innovations in the Swedish food sector are considered radical. Many are 'insufficient' to meet demands for lower costs, shorter orders and sustainability. The authors highlighted that Swedish food producers generally tend not to adopt an 'open innovation' mindset: they develop products mainly in isolation or in collaboration with partners internal or external to the supply chain rather than involving and explicitly addressing consumers' needs. By drawing on a range of further case studies, Bayona-Sáez et al. (2013) reflected on 'open innovation' in the Spanish food and beverage industry. Openness is understood as breadth and depth of information sources, breadth of co-operation agreements and external R&D expenditure. Breadth of information sources and co-operation agreements are associated with radical innovations but not with incremental innovations, which seem rather to depend on firms' internal capabilities.

1.4. Beyond technological invention: organisational innovation

Beyond technological innovation, organizational innovation within the food-processing industry has increasing implications for the competitiveness of firms and the sector as a whole. Although innovation is generally associated with R&D for technological change, the marketing literature has shown that for innovation to be successful (i.e. to improve performance) R&D is not enough on its own. Firms need to combine R&D with market and organizational strategies (Gupta et al, 1986, in Grunert et al., 1997).

Moreover, Camisón and Villar-López's 2014 review of manufacturing in Spain shows that organizational innovation favours the development of technological innovation capabilities and that both organizational innovation and technological capabilities for products and processes can lead to superior firm performance. Similar relationships are expected for the food-processing industry specifically.

As a key player in the process of agro-industrialization, food-processing firms are engaging in tighter vertical co-ordination and networking with participants in their supply chains, particularly agricultural producers. There is a gradual replacement of spot-market exchange by sophisticated forms of intermediation and co-ordination (e.g. complex contractual arrangements, labelling, certification) (Cook et al., 2008; Biénabe et al., 2013).

As quality requirements (not only for products but for processes) and the nature of products change through R&D, specific investments and tighter co-ordination are needed among transactors to define standards, production processes and mechanisms and thus guarantee conformity (Ménard and Valceschini, 2005).

In turn, organizational innovation could be seen as one of the catalysts connecting R&D in technological innovation and performance, as new products or new quality characteristics may not imply improved performance without a corresponding organizational innovation. Moreover, more vertically integrated environments are also expected to shape both the appetite and the orientation of R&D. Fortuin and Omta (2009) identified the structure of the sector as a driver for investing in R&D in the Netherlands (see Section 2.3).

[21] See also Nyström and Edvardsson (1982) for an earlier study. The authors analysed product innovations in the Swedish food-processing industry. Product development strategies were described and evaluated from both a company and a consumer point of view. Three types of company outcomes were focused on: technological, market and commercial success. Variables related to company success appeared to be firm size, ownership and research intensity. Strategic variables analysed in relation to success were use of technology, R&D co-operation and marketing.

1.5. Innovation–R&D–performance linkages

Alarcón and Sánchez (2013) investigated empirically the effects of spending on external or internal R&D activities and how this may affect the business performance of Spanish agro-food companies. Based on the Encuesta de Estrategias Empresariales en España (a comprehensive survey of business strategies in Spain) and an overall sample including more than 400 firms over the period 2000–2008, the study used econometric analyses, specifically quantile regression, to address the vast asymmetry among the variables and to identify non-linear relationships. As a general finding, the analysis confirmed positive effects of both internal and external R&D on business performance. Internal R&D was found to be especially important for enhancing the productivity of SMEs.[22] However, the hypothesis that the most profitable firms are those that spend the most on R&D (i.e. their success was driven by R&D) was rejected and no significant evidence of complementarity between external and internal R&D was found. The authors therefore concluded that the vast majority of (Spanish) agro-food firms have at most the capacity for only one type of R&D, either internal or external. This may point to the fact that innovating companies increasingly rely (or need to rely) on outsourcing their research activities to extramural contract research providers or research organizations (public and/or private). Flipse et al. (2013) studied this with a particular view on food technology contract research, thus identifying context-specific key performance indicators (based on a modified version of the Wageningen Innovation Assessment Tool and data on 72 individual innovation projects).

Another aspect arguably relevant to the link between R&D and productivity is the rate of general technological progress in a sector and its adoption at firm level, which is generally recognized as probably the most important source of improvement in the productivity and competitiveness of firms in any industry. While progress is arguably an essential prerequisite for the transfer of technology, Bradley et al. (1995) and others focused on the process of technology transfer within the food-processing industry, which was (at least in the case of Northern Ireland) prompted by a lack of research in this area. The analysis investigated innovation and identified a diffusion pattern for the uptake of innovations. It also obtained a measure for the rate of technology transfer and identified the principal factors influencing the process. The results indicated factors that could be used to accelerate the diffusion of new technologies: the education levels of managers, R&D expenditure and the economic return to innovation activities.

In this light, it is worth mentioning that innovating agricultural and food-processing firms – like innovating firms from any other sector – face the challenge of knowing when they will be able to appropriate the rents accruing from their innovations. In fact, only the future value of the rents creates an incentive to perform R&D and to innovate, and all innovations that are either imitated or improved upon by competitors prevent the innovating firms from capturing their rents. Arguably, agricultural and food products are rather easy to imitate and the enforcement of intellectual property rights (IPR) does not appear to be trivial in many cases.[23] In a conceptual paper, Ferreira et al. (2013) discussed cases such as when the innovator fails to capture rents from innovation. The authors observed boundary conditions under which protection guarantees appropriation.

---

22 See also Avermaete et al. (2004). The authors examined the determinants of product and process innovation in small food-processing firms and based their research on an in-depth survey of 177 firms located in six rural areas in the EU. Multiple logistic regression was applied to identify the drivers of product and process innovation in the firms. The results highlighted the key role of the skills of the workforce (and also, implicitly, the role of internal R&D for generating and accumulating tacit knowledge of the workforce), the firm's general investment in know-how and the use of external sources of information. However, it is remarkable that there was no evidence of a significant relationship between the characteristics of the entrepreneur and the firm's innovation performance.

23 Pardey and Alston (2011) point out that many companies in the sector draw on the more basic agricultural research conducted by public agencies and universities, much of which is not patentable (see p.3). Moreover, the outcomes of corporate R&D, owing to its very nature, often do not allow the creation of enforceable IPR of any kind.

A paradox emerges in that innovators benefit from networking and the 'bandwagon effect',[24] but not from total diffusion of the knowledge. While networks are excellent vehicles for innovation, the business and social ties connecting firms deepen the hazards associated with the appropriation of rents (the dilemma of 'open innovation'/jointly undertaken innovation activities). Although the study was not focused on agro-food businesses, the findings seem to have particular relevance for this industry, which has been widely confirmed (e.g. by Alston, 2010). A further key finding of Ferreira et al. (2013) is that the social rate of return to investments in agricultural R&D has been relatively high. Given the comparably low spending on R&D in agro-food businesses (as argued above), the question arises as to whether or not certain market failures particularly impede investments in R&D and innovation activities in this industry. The available literature does not provide an ultimate answer to this question, which points to the need for further investigation.

In summary, key aspects in the emergence of R&D and innovation activities in food processing seem to be intersectoral linkages, knowledge creation and technological flows along the value-added chain, common company structures (i.e. sector concentration and particularly company size distribution) and, overall, the existence and performance of a functioning sectoral innovation system.[25] For instance, according to the Italian National Statistics Institute (ISTAT), the country's food-processing sector is remarkably fragmented, with an average of 6–7 employees per firm and approximately 95% of all food-processing firms in the class with less than 10 employees (ISTAT, 2008). This obviously complicates the emergence of a well-functioning sector innovation system, as most of the companies simply do not reach the minimum capacity (and/or critical mass) to establish relationships at the system level and/or to carry out their own research activities.[26] The studies concerning SMEs and the relevance of R&D for their competitiveness, as discussed above, point in the same direction.

Beyond the characteristics of the corresponding sectoral innovation system, the quality of the regional innovation system (RIS) in which a given firm operates also matters, regardless of whether the business is high- or low-tech, small or large, etc. The literature suggests that traditional sectors are often only weakly integrated in high-tech socio-institutional environments, mainly owing to the incompatibility of the specific innovation modes of low- and high-tech industries. This aspect is tackled by Trippl

---

24 The bandwagon effect is a phenomenon whereby the rate of uptake of beliefs, ideas, fads and trends increases the more that they have already been adopted by others. In other words, the bandwagon effect is characterized by the probability of individual adoption increasing with respect to the proportion of those who have already done so. As more individuals/firms come to believe in something, others also 'hop on the bandwagon' regardless of the underlying evidence.

25 Innovation systems can be defined in a variety of ways: they can be national, regional, sectoral or technological. They all involve the creation, diffusion and use of knowledge. Systems consist of components, relationships among these, and their characteristics or attributes. National innovation systems are considered most commonly (see Freeman, 1988; Lundvall, 1988, 1992; Nelson, 1988, 1993; and many others). For sectoral innovation systems see, for example, Breschi and Malerba (1997), Malerba and Orsenigo (1990, 1993, 1995) and Malerba (2004). As in Porter's 'diamond' (Porter, 1990), the system definition here is based on 'industry' or 'sector', but, rather than focusing on interdependence within clusters of industries, sectoral innovation systems are based on the idea that different sectors or industries operate under different technological regimes that are characterized by particular combinations of opportunity and appropriability conditions, degrees of cumulativeness of technological knowledge and characteristics of the relevant knowledge base. These regimes may change over time, making the analysis inherently dynamic, focusing on the competitive relationships among firms by explicitly considering the role of the selection environment. With regard to specifics and facilitating agricultural innovation systems see, for instance, OECD (2012), World Bank (2007, 2012), Koutsouris (2012), Rajalahti et al. (2008) or EU SCAR Collaborative Working Group AKIS (2012). A general discussion of the agricultural innovation process is provided, for instance, by Sunding and Zilberman (2000), and Loebenstein and Thottappilly (2007) discuss agricultural research management issues.

26 See, for example, World Bank (2006, 2012) for comprehensive material on agricultural innovation systems and the corresponding role of R&D. Regarding specific country or regional dimensions, see Bokelmann et al. (2012) for a study of the agricultural innovation system in Germany, or Fraunhofer IVV and TU München (2010) for an inventory of R&D in the agro-food sector, challenges and possible solutions.

(2010) in a study focusing on the empirical case of the food industry located in the Vienna metropolitan region. The author provides evidence that the link between traditional industries and their high-tech contexts may be more complex than commonly understood and discussed in the literature. As a result of the study, it is highlighted that strong and weak forms of integration in the RIS co-exist, depending on the specific RIS dimension under consideration. Innovative companies in the local food sector embed themselves in a selective way in their regional institutional context; they make use of the scientific competences available within the RIS while at the same time tending to 'bypass' the RIS and tap into knowledge sources located outside the region.

Overall, when reviewing the available empirical investigations of R&D (and innovation) in agro-food industries it appears that most studies address only very specific aspects and/or rely on data or samples of rather limited scope. In fact, most consider only a certain country or a small part of the sector or certain firm types and, in essence, tend to be case studies. This is partly due to the lack of comprehensive data as outlined above. Nevertheless, there is an obvious need for further research to substantiate and generalize the findings of the available studies and by that means to close the corresponding gap in the empirical literature.

1.6. Measuring R&D and performance

Agricultural economists have used commodity market models (e.g. interaction between demand and supply) to represent the impact of agricultural research, beginning with Schultz (1953) and Griliches (1958) and with important subsequent contributions from Petersen (1967), Duncan and Tisdell (1971), Duncan (1972), Akino and Hayami (1975) and Scobie (1976) among others. The same implicit modelling approach is assumed in studies that infer a rate of return to R&D-based econometrically estimated productivity gains (e.g. Evenson, 1967) or use reduced-form approximations to measure gains from R&D (e.g. Griliches, 1958).

In the standard model of research benefits, as outlined in, for example, Alston et al. (1995), research causes a rightward (vertical) shift of the commodity supply curve against a stationary demand curve, leading to an increase in quantity produced and consumed and a lower price. The benefits are assessed using Marshallian measures of research-induced changes in research-induced consumers' and producers' surplus adjusted by expenditures on research. The total gross annual research benefits (GARB) depend primarily on the size of the (time-varying) research-induced supply shift and the scale of the industry to which it applies. Indeed, a common measure to approximate the gains from research as introduced by Griliches (1958) is GARB = kPQ, where k is the relative rate of vertical shift of the supply curve, P is the commodity price and Q is the annual quantity to which the supply shift applies. Other aspects of the analysis typically have second-order effects on the measures of total benefits but may have important implications for the distribution of the benefits between producers, consumers and other agents.[27]

Some issues in the literature relate to the methods used for measuring the primary determinant of total measured benefits: the research-induced reduction in the industry-wide unit cost of production as represented by the observed supply shift based on adoption rates combined with changes in experimental yields or commercial yields or on

---

[27] The distribution of the benefits between producers and consumers depends on the relative elasticities and functional forms of supply and demand curves and the nature of the research-induced supply shift (Alston et al., 1995, review these points). The nature of the research-induced supply shift has been a controversial issue in the literature because it is a key determinant of the distribution of benefits but it cannot be easily observed empirically. A critical issue in this context is the distributional effects among producers. In fact, even if producers as a whole benefit from research, those who do not adopt the new technology will not be likely to gain and may even end up worse off if the adoption by others leads to price reductions.

changes in total factor productivity (TFP). This aspect is often governed by the general nature of the analysis (e.g. evaluation of the benefits from the development of a particular varietal improvement compared with evaluation of a national agricultural research system, whether conducted *ex ante* or *ex post*) and the availability of data and other information.

Measures of the size and distribution of research benefits will be affected by various complications that can be introduced to extend the basic model. The introduction of international trade is a straightforward elaboration of the basic model, from which measures of welfare impacts for different spatial or market aggregates can be obtained. The model can be further extended by controlling for technological spillovers. More elaborate and complex multimarket models are applied if the market structure is to be vertically disaggregated, for instance to represent different stages of the marketing chain, or horizontally disaggregated, for instance to represent different geopolitical or spatial markets for a given product, or disaggregated by product (including different qualities of the same product). Alston et al. (1995) laid out the basic theory for these approaches and a number of studies have reported specific applications. Examples include Mullen et al. (1989), Freebairn (1992), Frisvold (1997), Wohglenant (1997), Davis and Espinoza (1998) and Zhao et al. (2000).

A further dimension for extensions to the basic model is to allow for departures from the case of publicly provided R&D and otherwise undistorted markets. The basic model assumes that the results from research are provided for free. Models that allow for proprietary technology (e.g. Moschini and Lapan, 1997) have not been used much in the applied work to date, and very little evidence is available on the distribution of benefits from private research between technology developers and providers and others, including farmers, consumers and agribusinesses.

Finally, it needs to be highlighted that the basic model, as a general notion, assumes competition in the market for the commodity and the absence of any other market distortions. Accordingly, some models that are set up to approximate research benefits have been extended to incorporate various types of market distortions, including those resulting from (i) the introduction of distortions associated with government policies, such as farm commodity programmes or trade barriers (e.g. Alston et al., 1988), and the failure to impose optimal trade taxes in the large-country case (e.g. Alston and Martin, 1995); (ii) the exercise of market power by middlemen (e.g. Huang and Sexton, 1996); and (iii) environmental externalities (e.g. Antle and Pingali, 1994). A general finding is that the main effect of a market distortion in this context is to change the distribution of research benefits, with comparatively small effects on the total benefits. Similar results apply to other types of extensions to the basic model that may be introduced to allow, for instance, for multiple markets or proprietary technology. As shown in the meta-analysis by Alston et al. (2000a,b), most of the studies reporting rates of return to agricultural R&D have used relatively simple concepts of benefits and have not dealt formally with any of the complications that can influence the total benefits but are more important as determinants of the distribution of benefits.[28]

1.7. Attribution

The existing literature points to the difficulties in capturing and correctly attributing R&D in models investigating the economic impacts of research in agriculture and/or food processing. This is comprehensively discussed by Alston and Pardey (2001), who argue that attribution problems in particular have bedevilled studies of the effects of research on agricultural productivity. The two principal areas of difficulty are (i) identifying the

---

28 Note that this summary of relevant concepts, measurement of R&D in agribusinesses and corresponding measurement issues is, to a large extent, taken from Alston (2010), Chapter 2.

component of productivity growth that is attributable to research-induced changes in knowledge and then further attributing responsibility among alternative public and private providers of R&D (the authors called it the 'spatial and institutional-cum-sectoral attribution problem') and (ii) identifying the research lag structure (the temporal attribution problem).

Similar problems arise when the analysis is focused on a particular innovation or is applied to all research undertaken by a national system, but the specifics differ as does the potential severity of the problems. Many studies assume implicitly or explicitly that all measured agricultural productivity growth is attributable to R&D (or perhaps even a particular source of R&D such as public R&D within a country). Increasingly, questions arise as to how much productivity growth might be attributable to factors other than organized R&D, including evolving weather patterns, institutional changes and economies of size and scope associated with the changing structure of the agro-food sector. As above, these questions remain wide open and require further research. However, Alston (2010) argued that it is likely that, in many cases, organized research has been the primary contributor to the productivity growth observed and the important issue is attribution among R&D sources. He explicitly distinguished between spatial and temporal aspects of the R&D attribution problem, which are discussed in brief below.

1.7.1. Spatial

Spatial attribution matters as we seek to match streams of benefits to streams of costs, and also because a large part of agricultural research is funded by public-sector entities that are defined geopolitically. The common statistical concepts, such as gross domestic expenditure on R&D (GERD), government budget appropriations for R&D (GBARD) and business expenditures on R&D (BERD), are of the same notion (see Eurostat website for corresponding definitions[29]). In turn, when it comes to information concerning business sector expenditures on R&D, especially those at company level, spending figures are aggregated at the company/parent company level but not necessarily following a territorial concept. In other words, in the case of corporations operating multinationally, it remains widely unclear where/in which country or region and what share of the total declared R&D has been carried out (i.e. to where the R&D expenditure should ultimately be attributed).

Whether or not they were concerned with spillovers, many empirical studies have imposed implicit or explicit assumptions about the spatial spillover effects of agro-food research based on geopolitical boundaries. More recently, agricultural economists have shown increasing interest in accounting for the fact that knowledge created within a particular geopolitical entity can have an impact on technology elsewhere, with implications that may matter to both the creators of the spillouts and the recipients of the spill-ins (see Alston (2002) for a review of this literature and Alston et al. (2010) for more recent discussion focused on the USA).

Admittedly, many studies have simply ignored spillovers. Nevertheless, beginning with Griliches (1957), some studies of adoption of individual technologies allowed for spatial spillovers among states and regions within a country. Some other studies have used regression-based methods to assess the overall effects of (agricultural) research on productivity using more aggregate (region- or state-specific as well as national) measures of R&D. Some of these have allowed for the impacts of spillover and those that did commonly found that these impacts were important. For example, Huffman and Evenson (1993) found that a sizeable share (45% or more) of the benefits from research conducted in US state agricultural experiment stations was earned as interstate spillovers. This measure was based on spatial proximity. Alston et al. (2010) found that

[29] Eurostat website: https://ec.europa.eu/eurostat

a similarly large share of total productivity growth in any US state was attributable to R&D conducted in other states or by the federal government.

In general, the analytical/conceptual decisions made in the relevant studies have been at least to some extent driven by the limitations of available data and the requirements for parsimonious models. Most analyses of national systems, irrespective of the method used, have implicitly assumed spatial spillovers. However, in their meta-analysis, Alston et al. (2000a) identified that less than 20% of studies were designed to allow for any spillovers. Alston (2010) argued that studies that do not allow for spillovers most likely suffer from some kind of specification bias.

1.7.2. Temporal

It takes a long time for research to affect production, and it may then affect production for a long time. Accordingly, one element of the attribution problem is identifying the specifics of the dynamic structure linking the spending on R&D, knowledge stocks and productivity change. A large number of previous studies have regressed a measure of agro-food production or productivity against variables representing corresponding research in some way, often with a view to estimating the rate of return to research or the leverage for productivity.[30] The specification of the determinants of the lag relationship between research investments and production, which involves the dynamics of knowledge creation, depreciation and utilization, is crucial. Nevertheless, only a few studies have presented much in the way of formal theoretical justification for the particular lag models they have employed in modelling returns to agricultural research. Until quite recently, it was common to restrict the (public) R&D lag length to less than 20 years. In the earliest studies, available time series were short and lag lengths were often very short. More recent studies have tended to use longer lags (wherever data allowed). Most studies have restricted the lag distribution to be represented by a small number of parameters, because both the time span of the dataset is usually not much longer than the assumed maximum lag length and the individual lag parameter estimates are unstable and imprecise given the high degree of collinearity between multiple series of lagged research expenditures.[31]

In their application using long-run state-level data on US agriculture, Alston et al. (2010) argued in favour of a gamma lag distribution model with a much longer research lag than most previous studies had found – for both theoretical and empirical reasons.[32] Their empirical work supported a research lag of at least 35 years and up to 50 years for US agricultural research, with a peak lag in year 24.[33] This comparatively long lag has implications for both econometric estimates of the effects of research on productivity and the implied rate of return to research. However, it has to be recalled that the research lag lengths reported here mostly correspond to public, and thus essentially fundamental, research, which arguably takes longer to translate into productivity changes than applied/close-to-the-market research as mainly carried out by private businesses.

---

30 A comprehensive reporting and evaluation of this literature is provided by Alston et al. (2000a); see also Schuh and Tollini (1978), Evenson (2002) and Alston et al. (2010).

31 As documented by Alston et al. (2000a), common types of lag structures used to construct a research stock include the de Leeuw or inverted-V (e.g. Evenson, 1967), polynomial (e.g. Davis, 1980; Leiby and Adams, 2002; Thirtle and Bottomley, 1988) and trapezoidal (e.g. Huffman and Evenson, 1989, 1992, 1993, 2006a,b; Evenson, 1996). A small number of studies have used freeform lags (e.g. Ravenscraft and Scherer, 1982; Pardey and Craig, 1989; Chavas and Cox, 1992).

32 The detailed arguments are laid out in Alston et al. (1995) and some earlier evidence is presented by Pardey and Craig (1989) and Alston et al. (1998). See also Huffman and Evenson (1989). Alston et al. (1998) discussed the issue of knowledge depreciation, drawing on the previous literature, and these arguments are restated and refined by Alston et al. (2008, 2010).

33 Alston et al. (2008) documented the adoption lags for particular agricultural technologies and their results are consistent with relatively long overall lags.

Nevertheless, the meta-analysis presented demonstrates that the average lag length tends to go well beyond the empirical horizon of most of the available time series data considered to be appropriate for investigating the R&D–productivity link in agro-food businesses. Hence, other concepts such as capturing R&D spending as a stock variable rather than as flows may serve. This turns attention from the question concerning the real time lag between spending on R&D and the corresponding impact on productivity. In turn, this puts emphasis on aspects such as accumulating knowledge through research activities (learning), tacit knowledge within firms/farms (fluctuation), amortization and 'depreciation' of research activities (i.e. knowledge becoming obsolete over time), which ultimately suggests the application of some kind of perpetual inventory approach for approximating the effective R&D input in a certain period.

1.8. Documented contribution of R&D on performance of food-processing businesses

There is a persuasive body of evidence demonstrating that the world as a whole and also individual nations have benefited enormously from productivity growth in agro-food businesses, a substantial amount of which has been enabled by technological change resulting from public and private investments in R&D. The evidence suggests that the benefits have been worth many times more than the costs. Alton (2010) argued that this is still so, even if we heavily discount the estimates because we suspect that they may have been upwardly biased, perhaps inadvertently through unfortunate choices of methods or limitations in the available data of the types discussed above.

In a nutshell, since the marginal benefit–cost ratios were much greater than 1.0, it would have been profitable to have invested (much) more in agro-food R&D. An implication is that, substantial government intervention notwithstanding, the world has systematically underinvested in agro-food R&D, and it is probably continuing to do so.[34] This is to some extent a paradox, since the importance of R&D (both publicly financed and business-sector activities) is thoroughly underlined in the literature and supported by statements from individual businesses and business associations. In fact, product innovation, on the one hand, and general technological progress in agriculture and food processing, on the other, are together highlighted as vital for addressing consumers' needs in terms of quality and diversity of foodstuffs and ultimately in ensuring global food security and sufficient nutrition for an increasing world population.[35] However, there still seems to be an insufficient number of (empirically based) studies that investigate and correspondingly underline the role of R&D (especially corporate R&D and innovation activities) in the trajectory of the agro-food sector and, especially, of R&D-investing firms compared with others.

In this context, the following quantitative exercise seeks to contribute to the literature by testing the economic impact of R&D spending for food producers, empirically investigating the differences in company performance attributable to the volume of R&D activities, thus studying corresponding time lags, trends and spatial aspects.

---

34 In essence, the World Bank (2008) arrives at the same conclusion (p.186), discussing why agricultural R&D is underfunded (pp.186ff) and possible ways to increase investments (pp.188ff).

35 See, for example, Huffman (2009).

Empirical exercise

1.9. Objective

This quantitative exercise investigates the role and impact of corporate R&D on firm performance in the food-processing industry in Japan, North America and the EU. We analyse the magnitude of inefficiency and explore the determinants of inefficiency for each firm against the frontier production function, which defines the maximum output achievable within the industry.

1.10. Approach and methodology

There is a rich literature attempting to conceptualize and define an efficient frontier function against which to measure the current performance of firms. Different approaches have been applied to identify efficient frontiers using both parametric and non-parametric methods. Both have strengths and limitations and choosing the most appropriate for a certain research question therefore appears to be a judgement call.

For instance, the parametric approach makes it possible to test hypotheses, takes account of statistical noise and provides parameter estimates of production factors, elasticities, etc., for possible further interpretation.[36] However, it imposes on a somewhat ad hoc basis on the functional form of the frontier to be estimated (although it can be flexible) and depends on assumptions concerning the distribution of the composed error term. In contrast, the non-parametric approach (a mathematical programming technique), which has been traditionally assimilated into data envelopment analysis (DEA), does not require such assumptions and is comparably easy to calculate. However, in general, some limitations remain regarding time series, slacks, relating inefficiencies to exploratory variables, etc.[37]

Looking at firm performance trends, we generally separate gains in efficiency from quality improvements by estimating a production frontier that distinguishes between virtual moves towards or away from the frontier (efficiency gains/losses) and shifts in the production possibility set – in other words, technical change (shift of the frontier or change in its shape) or catch-up. Regarding our main research questions and the length of our time series, we focus on whether or not, to what extent and how investments in R&D activities and/or capital stocks affect company performance in the food-processing industry. In fact, we are more interested in the magnitude of the corresponding effects and general trajectories than in firm-specific estimates.

Furthermore, the impact of the somewhat ad hoc selection of explanatory variables (such as capital accumulation, spending on R&D, persisting R&D intensity, main activity) on firm efficiency is tested. It is therefore necessary to control for time and eventually also for industry-specific effects. Taking the strengths and limitations of the method into account, this study applies the DEA technique. In fact, the results of the DEA frontier analysis can provide valuable insight into the role of corporate R&D for the agro-food industries and arguably also for policy-making, especially with respect to welfare implications. For instance, among efficient companies, productivity differentials can be reduced by improving the input mix/input qualities or by encouraging faster adoption of innovative technologies. By contrast, companies operating inefficiently could seek to improve the efficiency of the machinery they use and attempt to overcome the (external) restrictions that limit their individual businesses compared with their

[36] The stochastic frontier approach was introduced jointly by Aigner et al. (1977) and Meeusen and van den Broeck (1977) based on the seminal work by Farrell (1957). Comprehensive reviews of frontier approaches can be found, for instance, in Kumbhakar and Lovell (2000).

[37] See, for example, Coelli et al. (1998) for a fairly general introduction to efficiency and productivity analysis.

competitors (concerning, for instance, the institutional and financial framework, the infrastructure networks or the role of corporate R&D).

This approach, which benchmarks individual firms against the production frontier, is illustrated in the simple diagram of Figure 1. The frontier of the industry is constructed on the more performant firm given production factors Y1 and Y2 with firms A and B having inefficiencies with respect to the frontier.

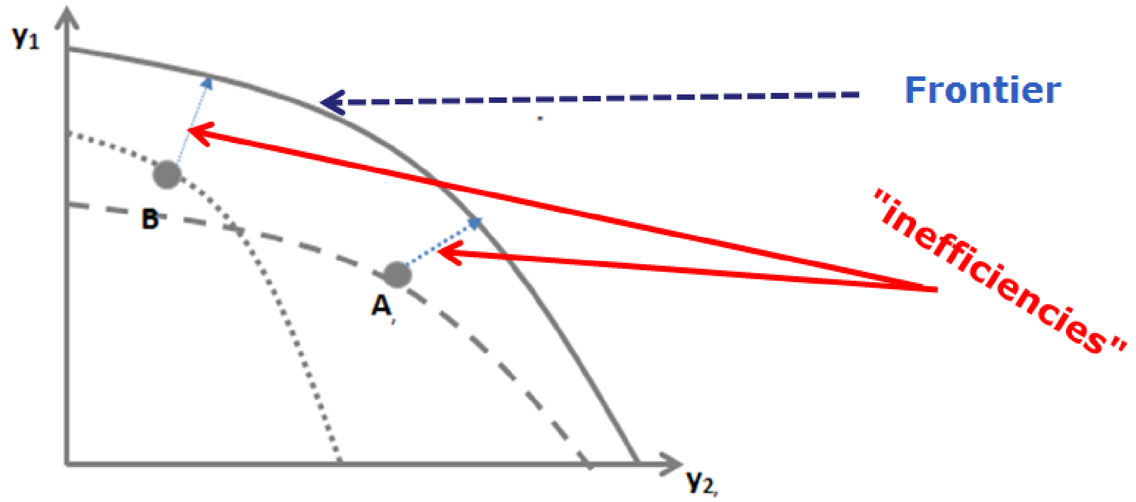


Figure 1 Production frontier of the sector and inefficiencies from individual firms A and B.

Source: own diagram

Methodologically, however, the assumption of a common frontier across countries and sectors is a sensitive issue. In general, the business framework and the technology appear to differ from industry to industry and country to country, especially if the companies under investigation are heterogeneous. Nevertheless, many studies do assume such a common frontier. In practice, estimating a common production function may lead to biased estimates of labour and capital elasticities. Some previous studies have tried to account for this bias by controlling for the quality of inputs (Koop et al., 2000; Limam and Miller, 2004). Others have explored the possibility of more than one frontier to explain 'excessively' different economies (see Orea and Kumbhakar (2004) for criticisms of using a single frontier).

This study avoids assuming a common technology across sectors by estimating at industry-specific technology level. The model used for the empirical analyses is outlined below.

1.10.1. The model

A frontier production function, in general, defines the maximum output achievable, given the current production technology and available inputs. If all industries produce on the upper boundary of the common production function (i.e. the frontier) with three inputs (*x*) – total cost of goods sold (COGS), physical capital (*C*) and labour (*E*) – the output of firm i in (sub)sector s at time t can be expressed as:

$$Y^*_{ist} = f(K_{ist}, E_{ist}, COGS_{ist}) \quad i = 1\ldots N;\ s = \text{food processing};\ t = 1991\ldots2009 \qquad (5)$$

where Y^*_{ist} is the frontier (maximum) level of output of firm i in industry s at time t. The output variable (*Y*) is the revenue at the firm level. The production technology is expressed by function *f*(.) and technically approximated by DEA. No assumptions regarding the error term will be made.

The frontier defined in equation (5) represents the maximum possible output given the inputs. The idea of the DEA approach is to estimate the frontier as well as inefficiency

(δ). An implicit but non-trivial assumption in this literature is that the leading industry itself is the frontier and the single benchmark for all other industries.

Basically, DEA consists of two steps. In the first step the maximum (max) output (Y^*) using the available data are calculated, e.g. max ($Y|$ data). This can be achieved by a linear programming model:

$$\begin{aligned} &\max_{\lambda_1,\lambda_2,\lambda_3} Y_1\lambda_1 + Y_2\lambda_2 + Y_3\lambda_3 \\ &s.t. \quad \mathbf{X}_1\lambda_1 + \mathbf{X}_2\lambda_2 + \mathbf{X}_3\lambda_3 \leq \mathbf{X}_2 \\ &\qquad \lambda_1 + \lambda_2 + \lambda_3 \qquad = 1 \end{aligned} \quad . \qquad (6)$$

The restriction $\lambda_1 + \lambda_2 + \lambda_3 = 1$ for the consideration of variable returns to scale. Other production structures require a different set-up of the restriction.[38] The optimal solutions $\lambda_1, \lambda_2, \lambda_3 > 0$ will provide an inner approximation of the production possibilities.

The second step consists of efficiency estimation. The inefficiency is defined by $\frac{Y^*}{Y} = \delta \; or \; Y^* = \delta\, Y$.

These two steps can be combined to the DEA model by calculating

$$\begin{aligned} &\max \delta \\ &\quad Y^*/Y = \delta \\ &\quad \lambda_1 Y_1 + \lambda_2 Y_2 + \lambda_3 Y_3 = Y^* \\ &\quad \lambda_1 \mathbf{X}_1 + \lambda_2 \mathbf{X}_2 + \lambda_3 \mathbf{X}_3 \leq \mathbf{X}_2 \\ &\quad \lambda_1 + \lambda_2 + \lambda_3 \qquad = 1 \end{aligned} \quad , \qquad (6)$$

or, after the definition of Y^* has been plugged in,

$$\begin{aligned} &\max \delta \\ &\quad \lambda_1 Y_1 + \lambda_2 Y_2 + \lambda_3 Y_3 = \delta Y \\ &\quad \lambda_1 \mathbf{X}_1 + \lambda_2 \mathbf{X}_2 + \lambda_3 \mathbf{X}_3 \leq \mathbf{X}_2 \\ &\quad \lambda_1 + \lambda_2 + \lambda_3 \qquad = 1 \end{aligned} \quad . \qquad (6')$$

This constitutes the DEA model in the formulation output distance function. Basically, it is the search for the proportionally factor (θ) that shifts Y_2 to the frontier.

In the literature, plenty of variations on the theme exist. Many of them have been described in the first part of the report.

a) Production, distance function (technical efficiency)
   Cost, profit, revenue function (allocative efficiency)
b) Input oriented, output oriented
c) Radial, nonradial measurement
d) Slacks, superefficiency
   Slacks: consideration of input waste for efficient companies
   Superefficiency (ranking among efficient enterprises)
e) Multiple inputs and outputs.

---

38 See first part of the report for more details.

In comparison with stochastic frontier analysis (SFA), the DEA approach pursued here has the following advantages: DEA needs no (strong) assumptions regarding the functional relationships (especially regarding the production function) and it is more flexible than SFA because no restrictions are required regarding the number of parameters. Thus, it is easy to deal with a whole range of inputs and outputs. However, the basic problems are that DEA is outlier sensitive and it is extremely data intensive to incorporate (non-parametric) statistical inference. Non-parametric approaches require far more observation until 'large number' theorems can be applied to conduct meaningful statistical tests. The required number of observations increases more than proportionally with the number of parameters (the 'curse of dimensionality').

An additional step consists in incorporating the determinants of inefficiency (z) (8) into a regression model. Examples of these z variables are R&D intensity, capital intensity and country dummies (capturing different institutional settings).

This leads to a typical two-stage approach. The first consists of a conventional DEA:

$$\hat{\delta}_i = \delta_i(\mathbf{X},\mathbf{Y} \mid T) = \max\left\{\delta > 0 \mid \delta \mathbf{y_i} \le \mathbf{Y\lambda},\, \mathbf{x_i} \le \mathbf{X\lambda},\, \mathbf{i'\lambda} = 1\right\} \quad , \qquad (6'')$$

followed by a second-stage regression:

$\delta_i = \mathbf{z_i\beta} + \varepsilon_i \ge 1$, where ε_i is an independent and identically distributed (i.i.d.) random variable, independent of z_i. (7)

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

$$\hat{\delta}_i = \mathbf{z_i\beta} + \xi_i \ge 1 \ . \qquad (7')$$

Usually a Tobit regression is applied to estimate the parameters of β. This procedure become necessary because the error term ε_i is truncated and not symmetrically distributed with mean 0. Examples of the z variables – also used in this study – are R&D intensity, capital intensity, time and country dummies (capturing different institutional settings). Note that, regarding the notations in equation (6), the output variable (*Y*) is the revenue at firm level. These z variables can be viewed as determinants of inefficiency. These observation-specific marginal effects allow detailed investigation of the impact of external factors on inefficiency.

Simar and Wilson (2007) point to several problems with this approach, concerning both stages of the procedure, and advocate the use of truncated regression:

1. Second-stage bias

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 second-stage bias, they suggest a bootstrap algorithm (see [6]). In addition to the second stage, the first stage is also biased:

$$\hat{\delta}_i = E(\hat{\delta}_i) + u_i \ .$$

Define the bias via

$$BIAS(\hat{\delta}_i) = E(\hat{\delta}_i) - u_i \ .$$

This gives:

$$\delta_i = \hat{\delta}_i - BIAS(\hat{\delta}_i) - u_i = \mathbf{z_i\beta} + \varepsilon_i > 1 . \tag{8}$$

Usually the bias as well as the *u* are ignored when conducting the second stage. This leads to biased estimates for the second stage.

2. First-stage bias

The bootstrap bias estimate equals the true bias plus a residual:

$$BI\hat{A}S(\hat{\delta}_i) = BIAS(\hat{\delta}_i) + v_i . \tag{9}$$

This can be used to construct a bias corrected estimator of *δ*:

$$\hat{\hat{\delta}}_i = \hat{\delta}_i - BI\hat{A}S(\hat{\delta}_i) . \tag{10}$$

Substituting (10) in (9) and the result in (8) provides:

$$\hat{\hat{\delta}}_i = \delta + v_i - u_i = \mathbf{z_i\beta} + \varepsilon_i > 1 .$$

Since *v* and *u* become negligible asymptotically the maximum likelihood (ML) estimation on

$$\hat{\hat{\delta}}_i \approx \mathbf{z_i\beta} + \varepsilon_i > 1 \tag{7''}$$

provides consistent estimates. As a solution to first-stage bias, Simar and Wilson (2007) proposed an alternative bootstrap algorithm (see [3]).

3. Double bootstrap algorithm

The steps of the double bootstrap procedure are as follows:

[1] Use the original data and compute $\hat{\delta}_i$ using (1)

[2] Use ML to obtain an estimate $\hat{\boldsymbol{\beta}}$ as well as $\hat{\sigma}_\varepsilon$ of (10) using the *m* < *n* observations $\hat{\delta}_i$ > 1

[3] Loop over the next four steps ([3.1]–[3.4]) L_1 times to obtain *n* sets of bootstrap estimates $1\left\{\hat{\delta}^*_{ib}\right\}_{b=1}^{L_1}$

[3.1] For each *i* = 1,...,*n* draw ε_i from the $N(0,\hat{\sigma}_\varepsilon{}^2)$ distribution with left truncation at $(1-\mathbf{z_i\beta})$

[3.2] Again for each *i* = 1,...,*n* compute $\delta_i^* \approx \mathbf{z_i}\hat{\boldsymbol{\beta}} + \varepsilon_i$

[3.3] Set $x^*_i = x_i$ and $y_i^* = y_i\hat{\delta}_i/\delta_i^*$ for all *i* = 1,...,*n*

[3.4] Compute $\hat{\delta}_i^* = \delta(\mathbf{x}_i, \mathbf{y}_i \mid T^*)$ for all *i* = 1,...,*n*. Here *T** denotes the set containing the transformed matrixes *X** and *Y** (see [3.3]).

[4] For each *i* = 1,...,*n* compute the bias-corrected estimator $\hat{\hat{\delta}}_i$ defined by (a) using the bootstrap estimates in 1 obtained in step [3.4] and the original estimate $\hat{\delta}_i$

[5] Use ML to estimate the truncated regression of $\hat{\hat{\delta}}_i$ on z_i, yielding estimates $\left(\hat{\hat{\boldsymbol{\beta}}}, \hat{\hat{\sigma}}\right)$

[6] Loop over the next three steps ([6.1]–[6.3]) L_2 times to obtain a set of bootstrap estimates $\mathrm{h}\left\{\left(\hat{\boldsymbol{\beta}}^*, \hat{\sigma}_\varepsilon^{\ *}\right)_b\right\}_{b=1}^{L_2}$

[6.1] For each i = 1,...,n draw ε_i from the $N(0, \hat{\hat{\sigma}}_\varepsilon^{\ 2})$ distribution with left truncation at $\left(1 - \mathbf{z_i}\hat{\hat{\boldsymbol{\beta}}}\right)$

[6.2] Again for each i = 1,...,n compute $\delta_i^{**} = \mathbf{z_i}\hat{\hat{\boldsymbol{\beta}}} + \varepsilon_i$

[6.3] Use ML to estimate the truncated regression of δ_i^{**} on z_i, yielding estimates $\left(\hat{\hat{\boldsymbol{\beta}}}^*, \hat{\hat{\sigma}}^*\right)$.

[7] Use the bootstrap values in h and the original estimates $\hat{\hat{\boldsymbol{\beta}}}, \hat{\hat{\sigma}}$ to construct estimated confidence intervals for each element of $\boldsymbol{\beta}$ and σ_ε.

$$Pr\left[-b_\alpha \le \left(\hat{\hat{\beta}}_j^{\ *} - \hat{\hat{\beta}}_j\right) \le a_\alpha\right] = 1 - \alpha$$
.

Step [3] and [4] employ a parametric bootstrap at the first stage (to get rid of the bias in δ). Step [6] employs a parametric bootstrap in the second stage.

1.11. Data

To appropriately answer the outlined research questions and test corresponding hypotheses, the empirical analyses should rely on company-level data, ideally covering a wide geographical cross-section (EU-27, America, Asia, etc.) and allowing investigation of firm/sector trajectories (i.e. time series information are required as well). Few databases allow for this. Considering the strengths and limitations of several potential sources of data, [39] it has been decided to draw upon Standard & Poor's (S&P's) Compustat dataset, [40] which contains data at firm level stemming from companies' audited annual/quarterly reports. Alternative data sources are discussed in the Appendix.

1.11.1. Representativeness

Compared with the overall population of companies, Compustat data tend to be biased towards large-scale businesses and to firms listed at stock markets (no 'private companies') since these firms are – in contrast with many others – required to publish annual reports (which is the main source of data for S&P's Compustat). Moreover, evidence from previous work with the same dataset suggests that there might be a geographical bias towards North American companies – in other words, EU and Asian (particularly non-Japanese) companies may be under-represented in the selected sample.

From the population of companies included in the Compustat database, all firms belonging to the agriculture sector and/or the food industry were selected, as a first

---

39 For instance, the Amadeus database may contain sufficient cross-section and time series firm-level data but provides information on R&D only for very recent years (if at all). The presumed emergence of the food-processing sector as medium-tech, evolving from formerly low-tech, could not be investigated based on such data. Another possible source of data could be the EU Industrial R&D Scoreboard (released by JRC-B3 Unit). This database contains fully consolidated firm-level data of top R&D investors in Europe and elsewhere (year of last audited report + 3 previous years). However, among the listed companies, there are too few belonging to the food industry.

40 For details see: www.compustat.com

step, covering the period 1991–2009 (geographical coverage: entire world). The resulting sample consisted of unbalanced longitudinal data comprising 189 companies assigned to the agriculture sector (industry code: 0xxx) and 1,118 companies assigned to the food-processing industry (industry code: 2xxx), and included information on 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 headquarters/where it is registered).

At this stage, firms assigned to the agriculture and food-industry sectors have been retrieved from Compustat because there is reason to believe that companies that were formerly purely agricultural businesses tend to agglomerate to an industrial production of commodities that are classified arbitrarily as food, food intermediates, renewable resources or traditional agricultural commodities. Moreover, a rising number of agribusiness companies have refocused their business towards the production of renewable resources meant to be used as fuel rather than as food (food input), such as oil seeds.

To double check for these tendencies, data from both industries have been screened (number of companies, number of employees, amount of capital expenditure, R&D expenditure). Further, the sector assignment in 2008 was matched to any 'historical' data (if available) to check whether or not there is indeed a tendency for some (presumably large-scale) companies to shift from the agriculture sector (agribusiness in general) to food-processing industries or vice versa. Comprehensive data screenings have been performed to search for such changes of sector assignment. However, although there is indeed some evidence in this regard, from the available data it cannot be reliably determined whether a company is better assigned to food processing or to agriculture. Hence, for reasons of consistency, it has been decided to proceed with the original industry assignment as given by Compustat, but to keep this subject in mind for the interpretation of results and for discussing potential biases.

Given the relatively scattered empirical coverage of companies belonging to agriculture (much fewer companies in the dataset belonged to agriculture than food processing) and, moreover, the fact that almost none of the companies from agriculture reported R&D expenditures, companies assigned to agriculture (industry code: 0xxx) were excluded. The remaining sample consisted of 1,118 firms (all assigned to the food-processing sector) with 6,670 observation points in total over time (entire world). These raw data had to be processed further.

The dataset does not distinguish between R&D conducted domestically and abroad. All companies' R&D expenditure was assigned to the country the company is registered to. However, since most of the R&D is in-house R&D expenditure, it is expected that the representativeness of the data is negligibly affected.

1.11.2. Currency conversion and price deflation

All variables in monetary units were converted to Euro using the 2007 end-of-year exchange rate.[41] In cases where no direct exchange rate to Euro was provided by Compustat, the corresponding currency was converted first to USD and then to Euro.

1.11.3. Missing values

To estimate the performance of companies in the food-processing sector (considering input–output relations at every observation point, e.g. for a certain firm in a given year), information is required on revenue or sales as a proxy for output and, moreover, on the

[41] Preference was given to end-of-year exchange rates because the period the annual reports refer to for most of the companies corresponds to the calendar year. Hence, end-of-year exchange rates are the closest to the reporting date and arguably may introduce the least bias.

relevant inputs (i.e. number of employees and expenditure[42] on capital and R&D). It appears that in many countries it was not compulsory to report number of employees or cost of employment in company annual reports. In fact, the withdrawn datasheet contained many blanks ('n.a.'), especially for Asian companies. However, labour input appears to be essential for considering firm performance. It was therefore decided to proceed as follows: where number of employees was missing but labour expenditure was available, number of employees was approximated using average wage levels taken from the International Labour Organization (ILO). Where information on the number of employees was available but missing on labour expenditure, labour expenditure was approximated using average wage levels taken from the ILO data. Where information on neither the number of employees nor total costs of employment (aggregated wages) was available, the corresponding observation (data line, not company) was excluded. Where revenue and/or capital expenditure data were missing, the corresponding observation had to be excluded as well. The sample was reduced significantly: out of 5,924 observation points in total (corresponding to the entire world), 2,491 reported expenditures on R&D different from zero.

1.11.4. Consistency and outliers

The methodological approach to be applied in this study (identifying production frontier functions), owing to its very nature, is very sensitive to outliers.[43] 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.[44] Hence, reducing the sample to a subsample comprising rather homogeneous countries/companies appeared advisable to ensure largely unbiased empirical results. Outlier observations may, however, still need to be excluded from the sample.

In this light, it has been decided to restrict the scope of the analysis to observations of companies registered in one of the following country groups: the EU (557 observations remaining), North America (the USA and Canada; 1,050 observations remaining) and Japan (1,341 observations remaining). The relatively even distribution of observations among these three macro-regions allows for a comparative analysis. Moreover, the remaining ~3,000 observations (307 companies) comprise an unbalanced dataset with an average of 10 observations per firm (length of time series), while company data from other world regions (to be disregarded) appeared far more scattered. Therefore, the resulting sample of these three macro-regions is assumed to be suitable for performing panel data analyses.

In about 50% of all observations (firm/year) in this sample, expenditure on corporate R&D was different from zero, which is comparable with the share of firms performing R&D worldwide (see above). Admittedly, in many of those cases where R&D expenditure was reported as different from zero, observations suggested fairly low/medium-low R&D intensity. However, some companies reported expenditure on R&D above 5% of revenues, which would allow them to be classified as high-intensity R&D companies (i.e. high-tech firms, according to the commonly applied classification).[45] Accordingly, the sample may serve for an analysis of the impact of R&D (intensity) on firm performance, with a significant control group of companies carrying out no R&D.

---

42 Capital expenditure will be used to calculate R&D (knowledge) stocks, applying the perpetual inventory method.

43 For a discussion of the sensitivity, strengths and limitations of the SFA see, for example, Kumbhakar and Lovell (2000) or Coelli et al. (1998).

44 However, country differences are likely to exist and – to some extent – can be captured by country dummies.

45 Note that in a comprehensive study on sector classification, Hatzichronoglou (1997) confirmed food-processing industries to be a low-tech industry. For an overview of the thresholds and a brief discussion see: www.oecd.org/dataoecd/32/17/41419823.ppt

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 excluded. Outliers were excluded according to the results of Grubbs' tests centred on the sectoral average growth rates of firms' R&D stock intensity (*K*/revenue) over the period of investigation.[46] Moreover, some further observations were excluded for reasons related to the computation of the R&D and capital stocks.[47]

Table 2 summarizes the final sample used in the report. After cleaning and processing the data, European companies are less represented than their 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 remains more balanced, including for European firms, easing comparison between macro-regions. To control for these data structures, we used dummy variables in our estimations, distinguishing between these two periods.

Table 2 Sample composition – observations per year and region

Year	EU	USA/Canada	Japan	Total sample
1991	2	30	0	32
1992	8	50	0	58
1993	10	49	0	59
1994	12	51	0	63
1995	13	51	0	64
1996	17	52	0	69
1997	25	53	0	78
1998	24	58	0	82
1999	26	55	91	172
2000	27	60	127	214
2001	30	59	134	223
2002	32	59	134	225
2003	35	61	136	232
2004	34	63	138	235
2005	35	67	143	245
2006	71	70	143	284
2007	74	72	142	288
2008	71	70	142	283
2009	11	20	11	42
Number of observations	557	1,050	1,341	2,948
Number of firms	85	79	143	307

Source: own compilation

46 See Section 3.3.5. for a definition of *K*. Notice that Grubbs' test – also known as a maximum normalised residual test – assumes normality (which is a desirable property anyway). Accordingly, we ran normality tests on the relevant variables (the assumption was never rejected). Results from both Grubbs' and normality tests are available upon request.

47 See equations (1) to (4); in the rare cases a negative g turns out to be larger in absolute value than the depreciation rate δ, the perpetual inventory method generates an unacceptable negative initial stock at time zero. The same happened (in a few cases) when in the initial year negative capital expenditures were reported (Capex was then set to zero).

It has to be stressed that the final sample of 307 firms is biased towards large companies (listed in the stock markets). This bias is due to the nature of the data source and has two important consequences. First, results cannot be easily generalized, as 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. Second, this '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 that, moreover, are scarcely or not engaged in R&D investment (Becker and Pain, 2002). Both consequences need to be kept in mind in the interpretation of the empirical results.

In terms of sectoral representation, observations from beverage companies are the most present, followed by mixed-activity or generalist food-processing firms and prepared-foods firms, accounting for 53% of the total sample. The rest of the subsectors account for between 4% and 9% (Table 3).

Table 3 Sample composition – observations per subsector

Subsector	Codes	Number of 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		2,948

Source: own compilation

1.11.5. Further data processing: stock variables

In accordance with related literature (see Jorgenson, 1990; Hulten, 1991; 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 by the cumulated stocks of capital and R&D expenditure and not only by current or lagged flows.[48] Accordingly, our pivotal impact variable is a firm's R&D stock (K) and our second impact variable is capital expenditure (C) captured as capital stocks.[49] Thus, considering per capita values (i.e. per number of employees) permits both the standardization of data and the elimination of firm size effects (see, for example, Crépon et al., 1998).

48 Using cumulated R&D and capital stocks – as in previous literature – overcomes a potential endogeneity problem that can arise if flows are used. See Section 2 for a comprehensive discussion of R&D time lags, dynamic lag structures and corresponding data and measurement issues.

49 Other explanatory variables like organizational innovation and skills (although not in the scope of this contribution) are surely important in explaining firm productivity growth (see, for example, Piva et al. 2005). Unfortunately, given data limitations, it was not possible to control for the important role of human capital.

In this framework, knowledge (R&D) and physical capital stocks were computed using the perpetual inventory method based on the following formulas:

$$K_{t0} = \frac{R\&D_{t0}}{g_{s,c}(K) + \delta_j}, \qquad (1)$$

$$K_t = K_{t-1} \cdot (1 - \delta_j) + R\&D_t, \text{ with } t = 1991, \ldots, 2009, \qquad (2)$$

$$C_{t0} = \frac{I_{t0}}{g_{s,c}(C) + \varphi_j} \text{ and} \qquad (3)$$

$$C_t = C_{t-1}(1 - \varphi_j) + I_t, \qquad (4)$$

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

The OECD Analytical Business Enterprise Research and Development (ANBERD) database and the OECD STAN database 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 relevant sector (food processing; s) and per country (c). For some European countries, these databases did not report or allow for the calculation of specific growth rates for R&D and capital stocks. The corresponding European averages were assumed in these cases instead. For the USA, Canada and Japan, however, the growth rates were taken from the literature.[50]

In general, different depreciation rates (δ) and (φ) for K and C should be assumed for high-, medium- to high-, medium-to low-/low-intensity R&D industries (sectoral groups (j)). In fact, technologically advanced sectors are characterized (on average) by shorter product life cycles and faster technological progress, which together accelerates the obsolescence of current knowledge and physical capital.[51] 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- to high- and medium- to low-/low-tech sectors,[52] with the latter (δ = 12%, φ = 4%) to be applied here to the food-processing industry.

1.11.6. Descriptive statistics

Table 4 presents some descriptive statistics of the final restricted sample. From this, some generalizations can be made. For instance, the heterogeneity among the observed companies within and across the macro-regions is notably high (see standard deviations and minimum/maximum of each variable). The assumed over-representation of large-scale companies seems to be confirmed; for example, the mean number of employees is 2,211 in Japan and 15,293 in the EU. Nevertheless, in each macro-region, there are also a number of small and even micro-companies (see minimum of employment variable).

The mean R&D intensity (R&D/sales) in all macro-regions is above 1%, with the EU reporting the highest (~6%). This allows the classification of the companies/sectors as

---

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

51 Physical capital also embodies technology, and rapid technological progress makes scrapping more frequent.

52 The resulting weighted averages (across sectors) were 15.6% for the R&D stock and 6.0% for the capital stock respectively; these values are very close or identical to the 15% and 6% commonly used in the literature (see Musgrave, 1986; Bischoff and Kokkelenberg, 1987; and Nadiri and Prucha, 1996, for physical capital; Pakes and Schankerman, 1986; Hall and Mairesse, 1995, and Hall, 2007, for knowledge capital).

medium-tech (or even medium- to high-tech).[53] Considering the median R&D intensity rather than the mean, the R&D/sales ratios do not change significantly in number in Europe and the USA/Canada, but they drop below 1% in Japan. However, regarding the number of companies actually performing R&D (number of observations with R&D expenditures different from zero), evidence suggests that the perception of whether or not R&D is important for the food-processing business differs between the macro-regions. In fact, in the EU and the USA/Canada few companies perform R&D at all (but those that do have significant spending), while in Japan the share of companies engaged in R&D activities is much higher (~90% but with lower individual expenditures).

In general, according to the descriptive statistics, the companies active in the food-processing sector in the EU and in the USA/Canada seem to be fairly similar: EU companies are, on 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 the USA/Canada and comparable figures in terms of spending on R&D and capital (including their accumulated stocks). In contrast, Japanese firms appear smaller, less profitable and more inclined to do corporate R&D, but, on average, with a lower financial commitment. This needs to be recalled when interpreting the frontier estimations and doing cross-country comparisons.

[53] Note that the average of R&D intensity of food-processing firms across EU was estimated to be at about 0.27. For an overview of thresholds and a brief discussion see: www.oecd.org/dataoecd/32/17/41419823.ppt

Table 4 Final restricted sample – descriptive statistics of main variables

Variable	Mean	Standard deviation	Minimum	Maximum	Observations
Total sample					2,948
Revenue	2,308.3	5,192.3	0.4	51,514.0	
COGS costs	1,443.5	3,295.6	0.4	47,137.0	
R&D expenditure	89.7	451.7	0.0	7,290.3	
Capital expenditure	1,286.4	2,996.3	0.0	25,846.0	
Employees	10,610	31,443	2	486,000	
EU					557
Revenue	2,705.8	6,602.6	0.4	51,514.0	
COGS costs	1,561.2	3,323.9	0.4	22,873.0	
R&D expenditure	175.6	926.9	0.0	7,290.31	
Capital expenditure	1,768.9	4,020.4	0.0	25,846.0	
Employees	15,292.7	36,441.3	2.0	269,000.0	
USA and Canada					1,050
Revenue	3,684.8	6,607.0	1.7	50,659.0	
COGS costs	2,309.5	4,578.3	1.0	47,137.0	
R&D expenditure	72.5	266.4	0.0	2,476.0	
Capital expenditure	1,839.9	3,584.2	0.0	24,759.0	
Employees	18,054	43,375	2	486,000	
Japan*					1,341
Revenue	1,065.3	1,983.5	5.0	15,913.0	
COGS costs	716.6	1,330.7	2.0	9,785.7	
R&D expenditure	67.5	181.5	0.0.	1,642.2	
Capital expenditure	652.6	1,497.7	0.0	13,127.0	
Employees	2,211	4,203	16	36,554	

*1999–2009 only

Source: own compilation

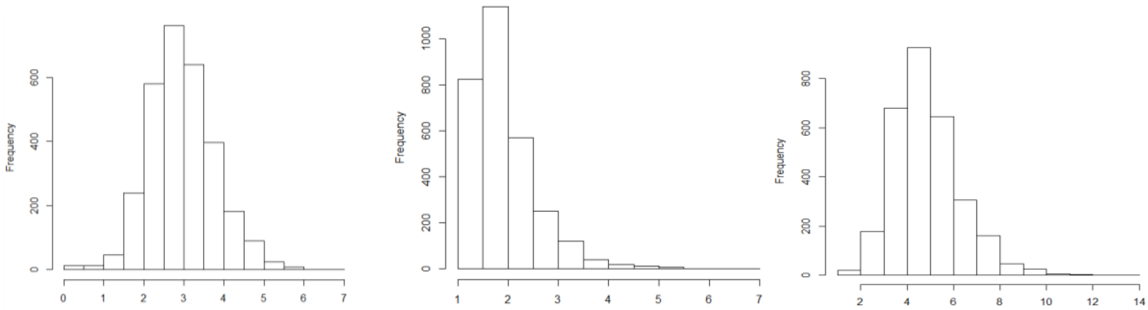
1.12. Results

1.12.1. The magnitude of inefficiency

We ran an output-oriented efficiency model – variable returns to scale (VRS) – with a simple specification consisting of one output and three inputs. Inputs are capital stock (*C*), labour (number of employees, *E*) and total cost of goods sold (COGS). The output is 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 2. In general, the figure shows that the inefficiency distribution is skewed to the left (panels (b) and (c), indicating that most of the companies operate relatively close to their frontier. Very high inefficiencies were found for only a few companies. Moreover, panel (a) presents 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 parameters in the second step. Panel (b) presents the inefficiencies calculated with the adjusted technology *T** (see [3.3]). Finally, panel (c) presents the unbiased estimator (distribution) of the inefficiency.

(a) (b) (c)



Inefficiency units Inefficiency units Inefficiency units

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

Figure 2 Different inefficiency estimates and estimated bias, frequencies.

1.12.2. The determinants of inefficiency

The basic hypothesis of the second stage is that R&D has a positive impact on firm performance. The determinants of inefficiency will be captured by the knowledge base of a company, for example:

$\delta = f(\text{knowledge base})$

The knowledge base depends on (i) own R&D and (ii) knowledge created elsewhere (universities, research institutes, companies) and that diffuses into the public domain

There is only one variable that measures companies' own R&D expenditure (z), whether the research expenditures are intra- or extramural. The information is usually available when companies are required to publish their investments. Although it can be safely assumed that large companies in all countries perform some R&D, 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 will bias the results. However, total lack of information on R&D is less severe than expected. Given the basic hypotheses, the impact of R&D on performance might be less significant because firms that do not report but conduct research should be more efficient than expected.

The hypothesis can also be stated as follows: (i) $\frac{\partial Y^*}{\partial z} = -\frac{\partial \delta}{\partial z} > 0$.

Regarding knowledge created elsewhere (technological opportunities), a firm's own R&D has an impact not only on revenues directly but, in addition, affects the technological opportunities of the firm. This relation is captured by Cohen and Levinthal (1989):

$$k^i = \theta(z^i, \beta)\left[\sum_{j \neq i} \mu\, z^j + T\right].$$

Here the firm's technological opportunities consist of two parts: knowledge external to the sector (T) (universities, public research institutes) and existing knowledge of competitors, which diffuses to some extent into the public domain (μ). The degree of openness (μ) depends on institutional regulations protecting firm-specific knowledge and also the type of technology.

Public knowledge can be used by the firm according to a coefficient of absorption (Θ). This coefficient depends on the height of the R&D expenditure, z, as well as the characteristics of the scientific and technological foundations. In addition, it is determined by the ease with which this knowledge can be absorbed. The coefficient β reflects the interference in a firm's own R&D expenditures from knowledge external to the firm. It is defined in such a way that a higher value of β increases the productivity of a firm's own research expenditure ($\theta_{z^1\beta} > 0$).

In order to make this effect operational, we include regional dummy variables in the estimation:

(ii) $\frac{\partial\delta}{dum\_JAP} < 0$ (iii) $\frac{\partial\delta}{dum\_US} < 0$

(iv) $\frac{\partial\delta}{dum\_EU15} < 0$ (v) $\frac{\partial\delta}{dum\_NMS} > 0.$

We expect that the USA and Japan have a favourable knowledge base to conduct R&D and that this knowledge base finds its expression in better firm performance (ii and iii). Some indication of this can be seen in Table 4, which shows that Japan and the USA have the highest research expenditure compared with outputs. The same effect can be expected for the old EU Member States (EU15) (iv). Similar to Japan and the USA, they belong to the group of countries with a highly developed research infrastructure. Given the structural difficulties of new EU Member States (NMS) from eastern Europe in particular, related to their history of planned economies, the research systems in these countries are likely to be less developed and thus attain lower productivity levels (v). 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 the USA (Chan-Kang et al., 1999; in Fuglie et al., 2011).

To control for the R&D environment of firms other than with regional dummies, the contemporaneous general public R&D investment per capita is also introduced (government sector GERD, Euro equivalent, 2007 constant prices). The time lags and dynamic effects (e.g. see Andersen and 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 and the period after 2004, with the 2000–2004 period serving as reference.

1.12.3. Estimated results

The estimated results of the pooled truncated regression are reported in Table 5. We 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 (USA, 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 presented with their unbiased estimators only. The extended first model (1B) also considers squared values of private R&D to capture the change in marginal gains from additional investment in private R&D.

The second set of models (2A and 2B) considers sectoral dummies instead of regional dummies, with firms specialized in grain processing used as the reference subgroup. Model 2B expands 2A by adding squared values of private R&D. The third set of models (3A and 3B) adds both regional and sectoral dummies in the estimated equation. Again, model 3B expands 3A by adding squared values 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 – to capture whether or not the impact of private R&D varies depending on region and sectoral circumstances, respectively. That is, the fourth set of models (4A and 4B) includes interaction variables between private R&D and regional dummies, while the fifth set of models (5A and 5B) includes interaction variables between private R&D and sectoral dummies.

The estimates largely confirm the hypothesis that private R&D has a positive effect on the performance of food-processing firms (i.e. it reduces inefficiency). 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 also makes a statistically significant contribution to performance. These results are consistent across all estimated models.

Private R&D investing seems to affect performance more positively in Canada (the reference country) than in the USA, Japan or EU15 countries (4A and 4B). The estimated coefficient for NMS is not significant in both models where the interaction variables between private R&D and regional dummies are considered (4A and 4B). These results suggest that additional R&D investment in Canada and NMS would produce greater firm efficiency gains than in the USA, Japan or EU15. Regarding subsectoral sensitivity to R&D investment on firm performance (5A and 5B), some subsectors (dairy, meat processing, oils and sugar) seem to be more responsive to R&D investment and more statistically significant than the reference sector (grain). In contrast, processed-food sectors are less sensitive to R&D investment, whereas the remaining subsectors 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 than during the 1990s. In terms of regional variation of firm performance, the estimates suggest that Japanese, US and EU15 firms are more efficient than 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 relative to Canadian peers and hence firms from other countries.

Firms operating as generalists in the food-processing sector tend not to show a statistically significant difference from the reference group (grains). In most models, this is also the case for dairy and sugar-related firms, with some insignificance for oil and canned producers. However, firms specializing in meats, bakery and prepared foods tend to be less efficient that those involved in grains.

Table 5 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*	-09157*	−107639*	−108921*	-09767*	−11729*
(R&D, perpetual inventory)²			0.0447*		0.0532*		00386*		01176*		00810*
Government sector GERD/capita	*−0.0023*	−0.0026*	−0.0028*	−0.0040*	−0.0041*	−0.0062*	-00054*	−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' dummies	*0.1187*	0.1938*	0.1852*	0.2708*	0.2827*	0.0904	0.1029	0.0904	0.0768	0.0861	0.0790
Post-2004 dummies	*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 × R&D								10.2002*	9.9897*		
USA × R&D								10.1015*	9.8361*		
(EU12, NMS) × R&D								−0.2317	−0.5675		
EU15 × R&D								9.9956*	8.7063*		
Dairy × R&D										−1.5265*	−1.5851*
Canned × R&D										−0.1390	−0.0883
Beverages × R&D										0.2183	0.1948
General × R&D										0.1830	−0.4624
Meats × R&D										−9.0025*	−9.1332*
Oils × R&D										−4.4689*	−4.5715*
Bakery × R&D										−0,8573	−0,8754
Prepared foods × R&D										0,5644*	0,4738*
Sugar × R&D										−1,2186*	−1,1682*

*Statistical significance at 5%

Source: own calculations using R v2.14 with FEAR package

Lessons from the empirical exercise

1.13. Approach/theoretical and methodological lessons

DEA is a widely applied approach in the literature to estimate firm productivity. One of its advantages is the fact that it allows the analysis to be performed without imposing assumptions about the form of the production technology or its functional form. It is a non-parametric technique and the approach does not impose restrictions on the number of parameters required. Moreover, it is flexible as it allows multiple inputs and outputs.

However, using DEA implies treating observations as non-stochastic. DEA is sensitive to outliers; therefore, it requires an in-depth preparation of the data, with implications for the structure of the sample.

The estimation of the common production frontier implicitly assumes that all companies have access to the same technology and produce under virtually the same technological restrictions. Although we have attempted to capture some aspects, such as regional and subsector variations, with regional and sectoral dummies, it is likely that some of the firm heterogeneities were not fully controlled for and thus potentially affect the estimated results.

The bootstrapping procedure applied in the report may have a twofold effect: it may both correct the bias in (in)efficiency estimates from the DEA and generate unbiased estimates for (in)efficiencies in the truncated regression. The procedure makes it possible to bias-adjust the coefficient estimates and calculate proper confidence intervals for statistical inference. However, bootstrapping tends to affect the structure of the data, potentially generating other forms of bias through overmanipulation 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 considering the available data.

1.14. Data issues

Data availability, as highlighted in the literature, remains a primary constraint, preventing in-depth and more nuanced analysis of the implications of R&D for firm performance. In this case, consistent reporting of R&D by firms in given countries is still elusive and prevents a reliable estimation of the magnitude of inefficiencies. The nature of data is also challenging as firms may operate in multiple sectors, blurring the boundaries between the sectors and their associated resources. The available data aggregate R&D investments for the company as a whole and do not specify the sectors or activities to which they were allocated.

The lack of data on small and medium-sized firms in the available database prevents the extrapolation of results to the whole sector.

Regarding the determinants of inefficiencies, the analysis falls short of capturing institutional and market structure implications for R&D effects (e.g. vertical integration), meaning that it is not possible to identify more nuanced effects of R&D.

The analysis of the role of consumer-driven R&D (e.g. through demand for high-value food, environmental goods) and its implications for firm performance could not be addressed in this report owing to the lack of comparable data.

The results from this exercise provide only an overview of the links between R&D and the overall performance of food-processing firms. Such exercise precludes decomposing the impact of the structure and type of R&D on firm performance (e.g. process vs. product vs. organizational innovation; external vs. internal research).

1.15. The challenges of interpretation and causal relationships

The deviations from the production frontier that DEA generates are key to the analysis in this report, as this is the performance indicator potentially linked to the level of R&D investment. The estimated deviations of efficiency from the frontier are attributed to the inefficiency term, some of which are due to the low level of R&D investments (as our estimates suggest), some of which could be caused by other drivers that have not been fully accounted for in this study, while some could be due to noise, which is difficult to differentiate from the prime effect under scrutiny.

Achieving a higher level of detail on how R&D affects firm performance requires better data or a different approach. In some cases, increasing the detail of the analysis may restrict the use of quantitative approaches (such as DEA). Instead, a more focused, in-depth qualitative analysis of a narrowly defined industry and/or a case study approach might be more relevant or informative.

Conclusions and policy implications

Our firm-level data show that EU firms tend to be slightly smaller in terms of revenue, sales and number of employees than their North American competitors. However, they have similar ratios of net income/revenue and R&D expenditure to those from the USA/Canada. In contrast, Japanese firms appear smaller than EU firms, less profitable and more inclined to carry out corporate R&D but, on average, with less financial commitment.

Our econometric estimates confirm the hypothesis that investment in R&D influences firm performance: food-processing firms that invest in R&D tend to be closer to the efficiency frontier than those that do not invest in R&D (i.e. private R&D has a negative effect on inefficiency). The estimates also point to decreasing marginal returns in reducing inefficiency (increasing efficiency) through private R&D. Our results also suggest that general public R&D is also positively associated with the efficiency of food-processing firms.

When looking at the drivers of firm performance, country/region dummies capture differences and similarities in knowledge systems and the nature of sectors. Similarities can be detected in US and Japanese contexts. Furthermore, a less favourable eastern European (NMS) context relative to the performance of firms from old EU Member States is identifiable from the exercise. However, the results suggest that gains from additional investment in R&D could be greater in NMS than in old EU Member States or in the USA.

Despite the comprehensiveness of the analyses, the findings of this report have to be considered with some caution on account of the data limitations. The persistent lack of R&D reporting in certain countries in the EU may create biases in the estimated effects. Furthermore, the sample contains many large firms from the food-processing industry and small firms are under-represented. These data limitations do not allow full extrapolation of the results to the whole food-processing industry.

Overall, the results of this report show that R&D in the food-processing industry is associated with higher firm performance. At the same time, the sample used in this report includes medium-/high-tech (and large) food-processing firms, challenging the generally held view that the sector is a low-tech sector. Hence, growth opportunities could also be expected from this type of non-high-tech innovative sector. However, results that suggest heterogeneity in R&D effects across EU Member States may point to differences in the implications of innovation policies across EU regions.

References

Aigner, D.J., Lovell, K.C., Schmidt, P. (1977): Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6:1, pp.21–37.

Akino, M. Hayami, Y. (1975): Efficiency and Equity in Public Research: Rice Breeding in Japan's Economic Development. American Journal of Agricultural Economics, 57:1, pp. 1-10.

Alarcón, S., Sánchez, M. (2013): External and internal R&D, capital investment and business performance in the Spanish agro-food industry. Journal of Agricultural Economics, 64:3, pp.654–675.

Alston, J.M. (2002): Spillovers. Australian Journal of Agricultural and Resource Economics, 46:3(September), pp.315–346.

Alston, J.M. (2010): The benefits from agricultural research and development, innovation, and productivity growth. OECD Food, Agriculture & Fisheries Papers, No. 31, OECD Publishing.

Alston, J.M., Andersen, M.A., James, J.S., Pardey, P.G. (2010): Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending. New York, NY: Springer.

Alston, J.M., Chan-Kang, C., Marra, M.C., Pardey, P.G., Wyatt, T.J. (2000a): A meta-analysis of rates of return to agricultural R&D: Ex pede herculem? Washington DC, IFPRI Research Report No. 113.

Alston, J.M., Chan-Kang, C., Marra, M.C., Pardey, P.G., Wyatt, T.J. (2000b): Research Returns Redux: A meta-analysis of the returns to agricultural R&D. Australian Journal of Agricultural and Resource Economics, 44:2, pp.185–215.

Alston, J.M., Edwards, G.W., Freebairn, J.W. (1988): Market distortions and the benefits from research. American Journal of Agricultural Economics, 70:2(May), pp.281–288.

Alston, J.M., Martin, W.J. (1995): Reversal of fortune: Immiserizing technological change in agriculture. American Journal of Agricultural Economics, 77(May), pp.251–259.

Alston, J.M., Norton, G.W., Pardey, P.G. (1995): Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting. Ithaca, NY: Cornell University Press (reprinted by CAB International, 1998).

Alston, J.M., Pardey, P.G. (2001): Attribution and other problems in assessing the returns to agricultural R&D. Agricultural Economics, 25:2–3(September), pp.141–152.

Andersen, M.A., Song, W. (2013): The economic impact of public agricultural research and development in the United States. Agricultural Economics, 44: 287–295.

Antle, J.M. Pingali, P.L. (1994): Pesticides, productivity, and farmer health: A Philippines case study. American Journal of Agricultural Economics, 76(August), pp.418–430.

Avermaete, T., Viaene, J. Morgan, E.J., Crawford, N. (2003): Determinants of innovation in small food firms. European Journal of Innovation Management, 6:1, pp.8–17.

Avermaete, T., Viaene, J., Morgan, E.J., Pitts, E., Crawford, N., Mahon, D. (2004): Determinants of product and process innovation in small food manufacturing firms. Trends in Food Science & Technology, 15:10, pp.474–483.

Baregheh, A., Rowley, J., Sambrook, S., Davies, D. (2012): Innovation in food sector SMEs. Journal of Small Business and Enterprise Development, 19:2, pp.300–321.

Batterink, M.H., Wuppten, E.F.M., Omta, S.W.F. (2006): Factors related to innovative output in the Dutch agrifood industry. Journal on Chain and Network Science, 6:1, pp.31–45.

Bayona-Sáez, C., García-Marco, T., Sánchez-García, M., Cruz-Càzares, C. (2013): The impact of open innovation on innovation performance: The case of Spanish agro-food firms. In: Garcia-Martinez, M. (ed.): Open Innovation in the Food and Beverage Industry. Cambridge: Woodhead Publishing, pp 74-96.

Beckeman, M., Bourlakis, M., Olsson, A. (2013): The role of manufacturers in food innovations in Sweden. British Food Journal, 115:7, pp.953–974.

Becker, B., Pain, N. (2002): What determines industrial R&D expenditure in the UK? London: National Institute of Economic and Social Research.

Biénabe, E., Bramley, C., Kirsten, J. (2013). Quality-driven market innovations: social and equity considerations. In: Coudel, E., Devautour, H., Soulard, C.T., Faure, G., Hubert, B. (eds): Renewing Innovation Systems in Agriculture and Food: How to Go Towards More Sustainability? Wageningen: Wageningen Academic Publishers, pp.131–145.

Bischoff, C.W., Kokkelenberg, E.C. (1987): Capacity utilisation and depreciation-in-use. Applied Economics, 19, pp.995–1007.

Bokelmann, W., Doernberg, A., Schwerdtner, W., Kuntosch, A., Busse, M., König, B., Siebert, R., Koschatzky, K., Stahlecker, T. (2012): Sektorstudie zur Untersuchung des Innovationssystems der deutschen Landwirtschaft. Berlin: Bundesanstalt für Landwirtschaft und Ernährung (BLE).

Bönte, W. (2003): R&D and productivity: Internal vs. external R&D – Evidence from West German manufacturing industries. Economics of Innovation and New Technology, 12, pp.343–360.

Bradley, A., McErlean, S., Kirke, A. (1995): Technology transfer in the Northern Ireland food processing sector. British Food Journal, 97:10, pp.32–35.

Breschi, S., Malerba, F. (1997): Sectoral innovation systems: Technological regimes, Schumpeterian dynamics, and spatial boundaries. In: Edquist, C. (ed.): Systems of Innovation: Technologies, Institution and Organisations. London/Washington: Pinter.

Camisón, C., Villar-López, A. (2014): Organizational innovation as an enabler of technological innovation capabilities and firm performance. Journal of Business Research, 67:1(January), pp 2891-2902.

Capitanio, F., Coppola, A., Pascucci, S. (2009): Indications for drivers of innovation in the food sector. British Food Journal, 111:8, pp.820–838.

Capitanio, F., Coppola, A., Pascucci, S. (2010): Product and process innovation in the Italian food industry. Agribusiness, 26:4, pp.503–518.

Chan-Kang, C., Buccola, S., Kerkvliet, J. (1999): Investment and Productivity in Canadian and U.S. Food Manufacturing. Canadian Journal of Agricultural Economics 47, pp 105-118.

Chavas, J.-P., Cox, T.L. (1992): A nonparametric analysis of the effects of research on agricultural productivity. American Journal of Agricultural Economics, 74(August), pp.583–591.

Christensen, J.L. (2008): Knowledge-sourcing for product innovation in the food and drinks industry. In: Rama, R. (ed.): Handbook of Innovation in the Food and Drink Industry. New York/London: Haworth Press, pp.297–322.

Christensen, J.L., Rama, R., von Tunzelmann, N.V. (1996): Innovation in the European food products and beverage industry. Industry Studies of Innovation using CIS data. EIMS Project No. 94/111 (European Commission, DG XIII, Luxembourg).

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E. (1998): An Introduction to Efficiency and Productivity Analysis, 2nd ed. (2005). XVII, 350 pp.

Cohen, W., Levinthal, D. (1989): Innovation and Learning: The Two Faces of R & D. The Economic Journal, 99:397, pp 569-596.

Cohen, W.M., Klepper, S. (1996a): Firm size and the nature of innovation within industries: the case of process and product R&D. Review of Economics and Statistics, 78:2, pp.232–243.

Cohen, W.M., Klepper, S. (1996b): A reprise of size and R&D. Economic Journal, 106:437, pp.925–951.

Cook, M., Klein, P., et al. (2008). Contracting and organization in food and agriculture. In: Brousseau, E., Glachant, J.-M. (eds): New Institutional Economics: A Guidebook. Cambridge: Cambridge University Press, pp.292–304.

Corsino, M., Espa, G., Micciolo, R. (2011): R&D, firm size and incremental product innovation. Economics of Innovation and New Technology, 20:5, pp.423–443.

Crépon, B., Duguet, E., Mairesse, J. (1998): Research, innovation and productivity: an econometric analysis at firm level. Economics of Innovation and New Technology, 7, pp.115–158.

Davis, G.C., Espinoza, M.C. (1998): A unified approach to sensitivity analysis in equilibrium displacement models. American Journal of Agricultural Economics, 80, pp.868–879.

Davis, J.S. (1980): A note on the use of alternative lag structures for research expenditure in aggregate production function models. Canadian Journal of Agricultural Economics, 28, pp.72–76.

Duncan, R.C. (1972): Evaluating returns to research in pasture improvement. Australian Journal of Agricultural Economics, 16:3, pp.153–168.

Duncan, R.C., Tisdell, C. (1971): Research and technical progress: The returns to the producers. Economic Record, 47:117, pp.124–129.

Dutta, S., Lanvin, B. (2013): The Global Innovation Index 2013 – The local dynamics of innovation. Geneva, Ithaca, Fontainebleau: Cornell University, INSEAD (Institut Européen d'Administration des Affaires), WIPO (World Intellectual Property Organization) (co-publishers).

EU SCAR (Standing Group on Agricultural Research) Collaborative Working Group AKIS (Agricultural Knowledge and Innovation Systems) (2012): Agricultural knowledge and innovation systems in transition – a reflection paper. Brussels.

European Commission (2009): The 2009 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

European Commission (2010): EUROPE 2020: A strategy for smart, sustainable and inclusive growth. URL: http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:2020:FIN:EN:PDF

European Commission (2010): The 2010 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

European Commission (2011): The 2011 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

European Commission (2012): The 2012 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

European Commission (2013): The 2013 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

European Commission (2015): The 2015 EU industrial R&D investment scoreboard. Luxembourg: Publications Office of the European Union.

Evenson, R.E. (1967): The contribution of agricultural research to production. Journal of Farm Economics, 49(December), pp.1415–1425.

Evenson, R.E. (1996): Chapter 11: Two blades of grass: Research for U.S. agriculture. In: Antle, J.M., Sumner, D.A. (eds): The Economics of Agriculture, Volume 2, Papers in Honor of D. Gale Johnson. Chicago, IL: University of Chicago Press, pp.171–203.

Evenson, R.E. (2002): Chapter 11: Economic impacts of agricultural research and extension. In: Gardner, B.L., Rausser, G.C. (eds): Handbook of Agricultural Economics, Volume 1A: Agricultural Production. New York, NY: Elsevier.

Fagerberg, J., Mowery, D.C., Nelson, R.R. (2004). The Oxford Handbook of Innovation. Oxford: Oxford University Press.

Farrell, M.J. (1957): The measurement of productive efficiency. Journal of Royal Statistical Society, Series A, General 120, Part 3 (1957), pp.253–281.

Feigl, S., Menrad, K. (2008): Innovation activities in the food industry in selected European countries. Project report 'Traditional United Food Europe' (TRUEFOOD), WP 7.5: Traditional products and the economic impact of innovation. Straubing: University of Applied Sciences of Weihenstephan (ed.).

Ferreira, M.P., Serra, F.R., Maccari, E. (2013): When the innovator fails to capture rents from innovation. Instituto Politécnico de Leiria – Center of Research in International Business & Strategy (ed.), 'globADVANTAGE' Working Paper Series No. Nr. 101/2013.

Flipse, S.M., van der Sanden, M.C.A., van der Velden, T., Fortuin, F.T.J.M., Omta, S.W.F. (2013): Identifying key performance indicators in food technology contract R&D. Journal of Engineering and Technology Management, 30:1, pp.72–94.

FoodDrinkEurope (2015): Data & Trends 2014-2015. Based on OECD STAN and Eurostat data. URL: http://www.fooddrinkeurope.eu/uploads/publications_documents/Data_and_Trends_2014-20151.pdf

Fortuin, F.T.J.M., Omta, S.W.F. (2009): Innovation drivers and barriers in food processing. British Food Journal, 111:8, pp.839–851.

Fraunhofer IVV (Institut für Verfahrenstechnik und Verpackung) and Technische Universität München – Wissenschaftszentrum Weihenstephan (2010): Studie zum Innovationssektor Lebensmittel und Ernährung Im Auftrag des BMBF (2010).

Freebairn, J.W. (1992): Evaluating the level and distribution of benefits from dairy industry research. Australian Journal of Agricultural Economics, 36:2, pp.141–166.

Freeman, C. (1988): Japan: a new national system of innovation. In: Dosi, et al. (Eds.), Technical Change and Economic Theory. Francis Pinter, London, pp. 330–348.

Frisvold, G.B. (1997): Multimarket effects of agricultural research with technological spillovers. In: Hertel, T.W. (ed.): Global Trade Analysis. New York, NY: Cambridge University Press.

Fuglie, K.O., Heisey, P.W., King, J.L., Day-Rubenstein, K., Schimmelpfennig, D., Wang S.L., Pray, C.E., Karmarkar-Deshmukh, R. (2011): Research investments and market structure in the food processing, agricultural input, and biofuel industries worldwide. USDA-ERS Economic Research Report 130.

Garcia-Martinez, M., Britz, J. (2000): Innovation in the Spanish food & drink industry. International Food and Agribusiness Management Review, 3, pp.155–176.

Garcia-Martinez, M., Burns, J. (1999): Sources of technological development in the Spanish food and drink industry. A 'supplier-dominated' industry? Agribusiness, 15:4, pp.431–448.

Ghazalian, P.L., Furtan, W.H. (2007): The effect of innovation on agricultural and agro-food exports in OECD countries. Journal of Agricultural and Resource Economics 32(2), pp.448–461.

Gopinath, M., Pick, D., Li, Y. (2003): Concentration and Innovation in the U.S. Food Industries. Journal of Agricultural & Food Industrial Organization, 1:1, pp.1-23.

Gopinath, M., Vasavada, U. (1999): Patents, R&D, and market structure in the US food processing industry. Journal of Agricultural and Resource Economics 24(1), pp.127–139.

Griffith, R., Harrison, R., van Reenen, J. (2006): How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technological sourcing., The American Economic Review, 96:5, pp. 1859-1875.

Griffith, R., Redding, S., van Reenen, J. (2004): Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. Review of Economics and Statistics, 86:4, pp.883–895.

Griliches, Z. (1957): Hybrid corn: An exploration in the economics of technological change. Econometrica, 25, pp.501–522.

Griliches, Z. (1958): Research costs and social returns: Hybrid corn and related innovations. Journal of Political Economy, 66:1, pp.419–431.

Griliches, Z. (1979): Issues in assessing the contribution of research and development to productivity growth. Bell Journal of Economics, 10:1, pp.92–116.

Griliches, Z. (1995): R&D and productivity: Econometric results and measurement issues. In: Stoneman, P. (ed.): Handbook of the Economics of Innovation and Technological Change. Oxford: Blackwell, pp.52–89.

Griliches, Z. (2000): R&D, Education and Productivity: A Retrospective. Cambridge, MA: Harvard University Press.

Grunert, K.G., Harmsen, H., Meulenberg, M., Kuiper, E., Ottowitz, T., Declerck, F., Traill, B., Göransson, G. (1997): A framework for analysing innovation in the food sector. In: Traill, E., Grunert, K. (eds): Product and Process Innovation in the Food Industry. London: Blackie Academic and Professional.

Gupta, A.K., Raj, S.P., Wilemon, D. (1986): A model for studying R&D-marketing interface in the product innovation process, Journal of Marketing, 50, pp 7–17.

Hall, B.H. (2007): Measuring the returns to R&D: The depreciation problem. NBER Working Paper No. 13473. Cambridge, MA: National Bureau of Economic Research.

Hall, B.H., Mairesse, J. (1995): Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of Econometrics, 65, pp.263–293.

Hall, B.H., Mairesse, J., Mohnen, P. (2010): Chapter 22: Measuring the returns to R&D. In: Hall, B.H., Rosenberg, N. (eds): Handbook of the Economics of Innovation, Volume 2. Amsterdam: Elsevier, pp.1033–1082.

Hall, B.H., Rosenberg, N. (2010): Handbook of the Economics of Innovation, Volumes 1 and 2. Amsterdam: Elsevier.

Hatzichronoglou, T. (1997): Revision of the high-technology sector and product classification, OECD Science, Technology and Industry Working Papers, No. 1997/02, Paris: OECD Publishing.

Hayami, Y., Rutton, V.W. (1971): Agricultural Development: An International Perspective, 1st edn. Baltimore, MD: Johns Hopkins University Press. 1985 (2nd edition).

Huang, S.Y., Sexton, R.J. (1996): Measuring returns to innovation in an imperfectly competitive market: Application to mechanical harvesting of processing tomatoes in Taiwan. American Journal of Agriculture Economics, 78(1996), pp.558–571.

Huffman, W.E. (2009): Technology and innovation in world agriculture: Prospects for 2010-2019, Staff General Research Papers 13060, Iowa State University, Department of Economics.

Huffman, W.E., Evenson, R.E. (1989): Supply and demand functions for multiproduct U.S. cash grain farms: Biases caused by research and other policies. American Journal of Agricultural Economics, 71(August), pp.761–773.

Huffman, W.E., Evenson, R.E. (1992): Contributions of public and private science and technology to U.S. agricultural productivity. American Journal of Agricultural Economics, 74(August), pp.752–756.

Huffman, W.E., Evenson, R.E. (1993): Science for Agriculture: A Long-Term Perspective. Ames, IA: Iowa State University Press.

Huffman, W.E., Evenson, R.E. (2006a): Science for Agriculture: A Long-Term Perspective, 2nd edn. Oxford: Blackwell.

Huffman, W.E., Evenson, R.E. (2006b): Do formula or competitive grant funds have greater impacts on state agricultural productivity? American Journal of Agricultural Economics, 88:4, pp.783–98.

Hulten, C.R. (1991): The measurement of capital. In: Berndt, E.R., and Triplett, J.E. (eds.): Fifty Years of Economic Management. Chicago, IL: University of Chicago Press.

ISTAT (Italian National Statistics Institute) (2008): Struttura e dimensione delle imprese [Structure and dimension of firms]. Anno 2006. Statistiche in breve. Rome: ISTAT.

Jaffe, A.B. (1986): Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. American Economic Review, 76:5, pp 984-1001.

James, J.S., Pardey, P.G., Alston, J.M. (2008): Agricultural R&D policy: A tragedy of the international commons. University of Minnesota, College of Food, Agricultural and Natural Resource Sciences, Staff Paper Series, Staff Paper P08-08, InSTePP Paper 08-01; Sep 2008.

Jongen, W.M.F., Meulenberg, M.T.G. (2005): Innovation in Agro-food Systems. Wageningen: Wageningen Academic Publishers.

Jorgenson, D.W. (1990): Productivity and economic growth. In: Berndt, E.R., Triplett, J.E. (eds): Fifty Years of Economic Growth. Chicago, IL: Chicago University Press, pp.19–118.

Jorgenson, D.W., Gollop, F.M. (1992): Productivity growth in U.S. Agriculture: A postwar perspective. American Journal of Agricultural Economics, 74:3(August), pp.745–750.

Klotz, C., Fuglie, K., Pray, C. (1995): Private sector agricultural research expenditures in the United States: 1960-1992. ERS Staff Paper No 9525, Washington DC, U.S. Department of Agriculture, October.

Koop, G., Osiewalski, J., Steel, M.F. (2000): Modelling the sources of output growth in a panel of countries. Journal of Business and Economic Statistics, 18:3, pp.284–299.

Koutsouris, A. (2012): Facilitating agricultural innovation systems: A critical realist approach. Studies in Agricultural Economics, 114:2, pp.64–70.

Kumbhakar, S.C., Lovell, K.C.A. (2000): Stochastic Frontier Analysis. Cambridge: Cambridge University Press.

Kumbhakar, S.C., Ortega-Argilés, R., Potters, L., Vivarelli, M., Voigt, P. (2012): Corporate R&D and firm efficiency: Evidence from Europe’s top R&D investors. Journal of Productivity Analysis, 37:2, pp.125–140.

Leiby, J.D., Adams, G.D. (2002): The returns to agricultural research in Maine: The case of a small Northeastern experiment station. Northeastern Journal of Agricultural and Resource Economics, 20, pp.1–14.

Lichtenberg, F.R., Siegel, D. (1989): The impact of R&D investment on productivity – New evidence using linked R&D-LRD data. NBER Working Paper No. 2901. Cambridge, MA: National Bureau for Economic Research.

Limam, Y.R., Miller, S.M. (2004): Explaining economic growth: Factor accumulation, total factor productivity growth and production efficiency improvement. Department of Economics Working Paper Series, 2004-20, Connecticut University.

Loebenstein, G., Thottappilly, G. (2007): Agricultural Research Management. Dordrecht: Springer.

Loizou, E., Michailidis, A., Chatzitheodoridis, F. (2013): Investigating the drivers that influence the adoption of differentiated food products. British Food Journal, 115:7, pp.917–935.

Lundvall, B.-Å. (1988): Innovation as an interactive process: from user–supplier interaction to the national system of innovation, In: Dosi, et al. (Eds.), Technical Change and Economic Theory. Francis Pinter, London, pp. 349–369.

Lundvall, B.-Å. (Ed.) (1992): National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning. Pinter Publishers, London.

Malerba, F. (2004): Sectoral Systems of Innovation. Milano: Università Commerciale Luigi Bocconi.

Malerba, F., Orsenigo, L. (1990): Technological regimes and patterns of innovation: A theoretical and empirical investigation of the Italian case. In: Heertje, A., Perlman, M. (eds): Evolving Technology and Market Structure. Ann Arbor, MI: Michigan University Press, pp.283–305.

Malerba, F., Orsenigo, L. (1993): Technological regimes and firm behavior. Industrial and Corporate Change, 2:1(1993), pp.45–71.

Malerba, F., Orsenigo, L. (1995): Schumpeterian patterns of innovation. Cambridge Journal of Economics, 19:1(1995), pp.47–65.

Maredia, M., Byerlee, D., Ward, R. (1996): Econometric estimation of a global spillover matrix for wheat varietal technology. Agricultural Economics, 14:3, pp.159–173.

Meeusen, W., van den Broeck, J. (1977): Efficiency estimation from Cobb–Douglas production functions with composed error. International Economic Review, 18:2, pp.435–444.

Ménard, C., Valceschini, E. (2005). New institutions for governing the agri-food industry. European Review of Agricultural Economics, 32(3), pp.421–440.

Menrad, K. (2004): Innovations in the food industry in Germany. Research Policy, 33, pp.845–878.

Milbergs, E., Vonortas, N. (2005): Innovation metrics: Measurement to insight. White Paper of the National Innovation Initiative – 21st Century Innovation Working Group, IBM Corporation.

Moschini, G., Lapan, H. (1997): Intellectual property rights and the welfare effects of agricultural R&D. American Journal of Agricultural Economics, 79(November), pp.1229–1242.

Mullen, J.D., Alston, J.M., Wohlgenannt, M.K. (1989): The impact of farm and processing research on the Australian wool industry. Australian Journal of Agricultural Economics, 33, pp.32–47.

Musgrave, J.C. (1986): Fixed reproducible tangible wealth series in the United States, 1925-91. Survey of Current Business, 66, pp.51–75.

Nadiri, M.I., Prucha, I.R. (1996): Estimation of the depreciation rate of physical and R&D capital in the U.S. total manufacturing sector. Economic Inquiry, 34, 43-56.

Nelson, R., Winter, S. (1982): An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Nelson, R.R. (1988): National systems of innovation: preface and institutions supporting technical change in the United States. In: Dosi, et al. (Eds.), Technical Change and Economic Theory. Francis Pinter, London, pp. 309–329.

Nelson, R.R. (Ed.) (1993): National Systems of Innovation. A Comparative Analysis. Oxford University Press, Oxford.

NSF (National Science Foundation) (2008): National Science Board – Science and Engineering Indicators 2008 (two volumes). Arlington, VA: NSF.

Nyström, H., Edvardsson, B. (1982): Product innovation in food processing – a Swedish survey. R&D Management, 12:2, pp.67–72.

OECD (2002): Frascati Manual 2002: Proposed standard practice for surveys on research and experimental development – The measurement of scientific and technological activities. OECD Publishing. DOI: 10.1787/9789264199040-en

OECD (2009): Innovation to address food security. Paris: BIAC (Business and Industry Advisory Committee at OECD).

OECD (2012): Improving agricultural knowledge and innovation systems, OECD Conference Proceedings. OECD Publishing. URL: http://dx.doi.org/10.1787/9789264167445-en

OECD (2013): Agricultural innovation systems: A framework for analysing the role of the government. OECD Publishing. URL: http://dx.doi.org/10.1787/9789264200593-en

OECD/Eurostat (2005): Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data, 3rd edn – The Measurement of Scientific and Technological Activities. OECD Publishing. DOI: 10.1787/9789264013100-en

Oehmke, J.F., Crawford, E.W. (2002): The sensitivity of returns to research calculations to supply elasticity. American Journal of Agricultural Economics, 64:2, pp.366–369.

Orea, L., Kumbhakar, S.C. (2004): Efficiency measurement using a Latent Class Stochastic Frontier Model. Empirical Economics, 29:1, pp.169–183.

Ortega-Argiles, R., Potters, L., Voigt, P. (2009): R&D-intensive SMEs in Europe: What do we know about them? JRC-IPTS Working Papers on Corporate R&D and Innovation 2009-15, Institute of Prospective Technological Studies, Joint Research Centre.

Pakes, A., Schankerman, M. (1986): Estimates of the value of patent rights in European countries during the post-1950 period. Economic Journal, 96, pp.1052–1076.

Pardey, P.G., Alston, J.M. (2011): For want of a nail: The case for increased agricultural R&D spending. American Boondoggle. Washington, DC : AEI (American Enterprise Institute).

Pardey, P.G., Alston, J.M., Christian, J.E., Fan, S. (1996): Hidden harvest: U.S. benefits from international research aid. Food Policy Report. Washington DC, WA: IFPRI (International Food Policy Research Institute).

Pardey, P.G., Alston, J.M., Piggott, R.R. (2006a): Agricultural R&D in the Developing World: Too Little, Too Late? Washington DC, MA: IFPRI (International Food Policy Research Institute).

Pardey, P.G., Alston, J.M., Ruttan, V.W. (2010): The economics of innovation and technical change in agriculture. In: Hall, B.H., Rosenberg, N. (eds): Handbook of Economics of Technical Change. Amsterdam: Elsevier.

Pardey, P.G., Andersen, M.A. (2009): A long-run price index and the real cost of U.S. agricultural research. InSTePP Working Paper, St Paul, University of Minnesota.

Pardey, P.G., Beintema, N.M. (2001): Slow magic – Agricultural R&D a century after Mendel. International Food Policy Research Institute (ed.) – Agricultural Science and Technology Indicators Initiative. Washington DC, October 26, 2001.

Pardey, P.G., Beintema, N.M., Dehmer, S., Wood, S. (2006b): Agricultural research: A growing global divide? IFPRI Food Policy Report. Washington DC, WA: IFPRI (International Food Policy Research Institute).

Pardey, P.G., Craig, B. (1989): Causal relationships between public sector agricultural research expenditures and output. American Journal of Agricultural Economics, 71(February), pp.9–19.

Pardey, P.G., Craig, B.J., Deininger, K.W. (1994): A new look at state-level productivity growth in U.S. agriculture. In: Sundquist W.B. (ed.): Evaluating Research and Productivity in an Era of Resource Scarcity. Staff paper P94-2, Department of Agricultural and Applied Economics, University of Minnesota, February (Proceedings of the NC-208 Symposium at Orlando, Florida, March 1993).

Parisi, M., Schiantarelli, F., Sembenelli, A. (2006): Productivity, innovation creation and absorption and R&D – Microevidence for Italy. European Economic Review, 8, pp.733–751.

Petersen, W.L. (1967): Returns to investment in poultry research in the United States. Journal of Farm Economics, 49:3, pp.656–670.

Phillips, P.W.B., Karwandy, J., Webb, G., Ryan, C.D. (2013): Innovation in Agro-food Clusters – Theory and Case Studies. Wallingford, UK: CABI Publishing.

Piva, M., Santarelli, E., Vivarelli, M. (2005): The skill bias effect of technological and organisational change: Evidence and policy implications. Research Policy, 34:2, pp.141–157.

Porter, M.E. (1990): The competitive advantage of nations. Harvard Business Review 68:2(March–April 1990), pp.73–93. New York, NY: Free Press. (Republished with a new introduction, 1998.)

Rajalahti, R., Janssen, W., Pehu, E. (2008): Agricultural innovation systems: From diagnostics toward operational practices. Agriculture and rural development Discussion Paper No. 38. Washington DC, WA: World Bank.

Rama, R. (2008): Handbook of Innovation in the Food and Drink industry. New York/London: Haworth Press.

Ravenscraft, D., Scherer, F.M. (1982): The lag structure of returns to research and development. Applied Economics, 14, pp.603–620.

Scarpetta, S., Tressel, T. (2002): Productivity and convergence in a panel of OECD industries: Do regulations and institutions matter? OECD Economics Department Working Papers No. 342.

Schmalen C. (2004): Erfolgsfaktoren der Markteinführung von Produktinnovationen klein- und mittelständischer Unternehmen der Ernährungsindustrie. In: Hochschulschriften zur Betriebswirtschaftslehre (eds): Beschorner D., Volume 148 (Herbert Utz Verlag, Ulm).

Schuh, G.E., Tollini, H. (1979): Costs and benefits of agricultural research: State of the arts. World Bank – Staff Working Paper No. 360, Washington DC.

Schultz, T.W. (1953): The Economic Organization of Agriculture, New York, McGraw-Hill.

Scobie, G.M. (1976): Who Benefits from Agricultural Research?, Review of Marketing and Agricultural Economics, 44:4, pp. 197-202.

Simar, L., Wilson, P.W. (2007): Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, 136:1, pp.31–64.

Sunding, D., Zilberman, D. (2000): Chapter 4: The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In: Handbook of Agricultural Economics, 1 pp.207–261, Amsterdam: Elsevier.

Tepic, M., Fortuin, F.T.J.M., Kemp, R.G.M., Omta, S.W.F. (2014): Innovation capabilities in food and beverages and technology-based innovation projects. British Food Journal, 116:2, pp.228-250.

Thirtle, C.G., Bottomley, P. (1988): Is publicly funded agricultural research excessive? Journal of Agricultural Economics, 31, pp.99–111.

Trippl, M. (2010): Low-tech innovation in a high-tech environment? The case of the food industry in the Vienna metropolitan region. SRE – Discussion Papers, 2010/02, WU Vienna University of Economics and Business, Vienna.

USDA/ERS (United States Department of Agriculture Economic Research Service) (2010): Processing and Marketing: New products. Data from Datamonitor. URL: http://www.ers.usda.gov/topics/food-markets-prices/processing-marketing/new-products.aspx

Weindlmaier H. (2001): General aspects of food innovation management. In: Treillon, R. (ed.): Food Innovation Management from Idea to Success. Massy: Department of Food Processing and Engineering ENSIA.

Wilkinson, J. (1998): The R&D priorities of leading food firms and long-term innovation in the agro food system. International Journal of Technology Management, 16:7, pp.711–720.

Winger, R., Wall, G. (2006): Food product innovation: A background paper. Agricultural and food engineering working document 2. Rome: FAO (ed.).

Wohlgenannt, M.K (1997): The nature of the research-induced supply shift. Australian Journal of Agricultural and Resource Economics, 41:3, pp.385–400.

World Bank (2006): Enhancing agricultural innovation: How to go beyond the strengthening of research systems. Economic Sector Work Report. Washington DC, WA: World Bank, p.149.

World Bank (2007): Enhancing agricultural innovation: How to go beyond the strengthening of research systems. Economic Sector Work Report. Washington DC, WA: World Bank.

World Bank (2008): World Development Report 2008: Agriculture for development. Washington DC, WA: World Bank.

World Bank (2012): Agricultural Innovation Systems: An Investment Sourcebook. Washington DC, WA: World Bank, p.684.

Zhao, X., Griffiths, W. E., Griffith, G.R., Mullen, J.D. (2000): Probability distributions for economic surplus changes: The case of technical change in the Australian wool industry. Australian Journal of Agricultural and Resource Economics, 44, pp.83–106.

List of abbreviations and definitions

Abbreviation	Description
ASTI	Agricultural Science and Technology Indicators
BERD	business expenditures on research and development
BIAC	Business and Industry Advisory Committee
CIS	Community Innovation Survey
COGS	cost of goods sold
DEA	data envelopment analysis
EFIGE	European firms in a global economy
GARB	gross annual research benefits
GBARD	government budget appropriations for research and development
GERD	gross domestic expenditure on research and development
GMO	genetically modified organism
IMPRESA	Impact of Research on EU Agriculture
ILO	International Labour Organization
IPR	intellectual property rights
ISTAT	Italian National Statistics Institute
ML	maximum likelihood
NMS	new Member States
OECD	Organisation for Economic Co-operation and Development
R&D	research and development
RIS	regional innovation system
S&P	Standard & Poor's
SFA	stochastic frontier analysis
SMEs	small and medium-sized enterprises

SRA	scientific research on agriculture
STAN	Structural Analysis Database
TFP	total factor productivity
VRS	variable returns to scale

List of figures

List of tables

Appendix: data annexes

An alternative data source for our analysis in this report could have been the EU-EFIGE/Bruegel-UniCredit dataset. The EFIGE (European firms in a global economy) project, supported by the Directorate-General for Research of the European Commission through its Seventh Framework Programme (FP7), aims to explore firm dynamics in these areas:

- firm structure (company ownership, domestic and foreign control, management)
- workforce (skills, type of contracts, domestic vs. migrant workers, training)
- investment, technological innovation, R&D (and related financing)
- export and internationalization processes, market structure and competition
- financial structure and bank–firm relationship.

A survey of SMEs was conducted to get meaningful information about companies in seven EU Member States (Austria, France, Germany, Hungary, Italy, Spain and the UK). The information collected concerns the year 2008 and changes that occurred in the preceding years. However, the dataset is not a panel as only one year is considered. The data are extraordinarily rich because comparable information about innovative activities are included. However, the usefulness of the data for our analysis is rather limited because they mostly contain only qualitative assessments of innovative activities and not information about the intensity of these activities (e.g. research expenditure).The same holds true for information such as revenue, capital input and labour use. Moreover, because the information is confidential it is not possible to identify firms. Even a firm's affiliation to a specific sector is hidden. It is possible to identify that a firm belongs in country ***j*** to sector ***i***. However, it not clear which NACE (Statistical Classification of Economic Activities in the European Community) Revision 2 sector ***i*** relates to. Only guesses are possible. Because the EFIGE dataset is structured in this way, we did not consider the dataset for further analysis.

Another alternative could have been to rely on the Community Innovation Survey (CIS) for the analysis. Since the 1980s, a series of individual innovation surveys has been conducted based on the decision of the EU Member States to pool their efforts and create a methodology consistent with the Oslo Manual (OECD/Eurostat, 2005). However, on the one hand, there were inadequate methodological standards; on the other hand, the time frame was very tight. Nevertheless, it represented a significant step towards standardizing the process and was therefore an important contribution to the comparability of collected international data, with surveys outside the EU. The first survey had a very broad definition of 'innovative companies' so that a relatively large number of companies was included. In subsequent surveys, service innovations were also taken into consideration. In the latest survey, design innovations were included such as organizational changes or marketing.The survey is carried out in each country by appropriately authorized organizations based on EU-wide policies and the Oslo Manual (OECD/Eurostat, 2005). Typically, a sample of enterprises is taken, which is to be representative of industry, company size and region. In terms of company size, a number of companies with less than a certain number of employees are selected, and an attempt is made, at least in most countries, to include all the largest companies. The survey is conducted at the level of individual companies and each selected company will receive a questionnaire. Companies that organize their activities in separate legal business units could be interviewed more than once.

Micro-economic data can be obtained via the Safe Centre at the premises of Eurostat in Luxembourg or consulted anonymously via CD-ROM. Eurostat also offers access to an EU-wide dataset for selected countries. Some non-EU member countries carry out similar surveys with a comparable method. These include Canada, Australia, New Zealand and South Africa. However, for our analysis we had no access to the CIS database, so we had to rely on the information obtained from the Compustat dataset.

LB-NA-28249-EN-N

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub

Publications Office

doi:10.2788/85468

ISBN 978-92-79-63972-2